ESSAYS IN EMPIRICAL ASSET PRICING

by

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ESSAYS IN EMPIRICAL ASSET PRICING

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This dissertation contains three articles. In the first article, I review the literature on liquidity. I focus on various liquidity proxies and their effects on the equity returns while restricting the review to the set of top journals in finance since this literature is quite immense. In the second article, I investigate the relationship between expected returns and liquidity measures in Borsa Istanbul. Firm-level cross-sectional regressions indicate that there is a positive relationship between various illiquidity measures and one-month to six-month ahead stock returns. Findings are robust after using different sample periods and controlling for well-known priced factors such as market beta, size, book-to-market and momentum. The portfolio analysis reveals that stocks that are in the highest illiquidity quintile earn 7.2% to 19.2% higher risk-adjusted annual returns than those in the lowest illiquidity quintile. The illiquidity premium is stronger for small stocks and stocks with higher return volatility and it increases (decreases) during periods of extremely low (high) market returns. In the third article, I investigate the stock return exposure to various illiquidity risk factors through alternative measures of factor betas and the performance of factor betas in predicting the cross-sectional variation in stock returns. As a parametric test, a two-step procedure is utilized to directly calculate the monthly factor betas in the first stage and then, the sensitivity of stock returns to these previously estimated factor betas is calculated in the second. The regression results show that there exists a significantly positive link between illiquidity beta and future stock returns. The results are robust after controlling for market, size, book-to-market and momentum factors. The portfolio analysis reveals that stocks in the high-beta portfolio generate about 5% higher annual returns compared to stocks in the low-beta portfolio.

AMPİRİK VARLIK FİYATLAMASI ALANINDA MAKALELER

ALİ DORUK GÜNAYDIN

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Tez Danışmanı: Prof. Dr. K. Özgür Demirtaş

Anahtar Kelimeler: likidite; likidite riski; duyarlılık; gelişmekte olan piyasalar; öz sermaye karlılığı; varlık fiyatlaması

Bu tez üç makaleden oluşmaktadır. İlk makalede, likidite üzerine yazılmış literatür gözden geçirilmiştir. Bu inceleme, ilgili literatürün çok kapsamlı olması nedeniyle, finans alanındaki bir grup en iyi yayın ile sınırlandırılarak, çeşitli likidite ölçütlerine ve bu ölçütlerin hisse senedi getirileri üzerindeki etkilerine odaklanmıştır. İkinci makalede, Borsa İstanbul'da beklenen getiri ve likidite ölçütleri arasındaki ilişki araştırılmıştır. Şirket düzeyinde kesitsel regresyonlar, çeşitli likidite azlığı ölçütleri ile birden altı aya kadar gelecekteki hisse senedi getirileri arasında pozitif bir ilişki olduğunu göstermektedir. Bulgular; farklı örneklem aralıkları kullanılarak ve piyasa betası, büyüklüğü, defter-piyasa değeri oranı, momentum gibi bilinen fiyat faktörleri kontrol edilerek desteklenmiştir. Portföy analizi, en yüksek beşte birlik likidite azlığı diliminde yer alan hisse senetlerinin, en düşük beşte birlik likidite azlığı dilimindeki hisse senetlerine oranla, %7.2 ile %19.2 arasında riske göre ayarlanmış daha çok yıllık kazanç getirdiğini göstermiştir. Likidite azlığı primleri, küçük hisse senetleri ve daha yüksek getiri volatilitesi olan hisse senetlerinde daha güçlüdür; aşırı düşük (yüksek) piyasa getirilerinde yükselir (düşer). Üçüncü makalede, hisse senedi getirilerinin çeşitli likidite azlığı risk faktörlerinin etkisine hassasiyeti, alternatif faktör beta ölçütleriyle araştırılmıştır ve hisse senedi getirilerinde kesitsel varyasyonları ön görebilmek için faktör betaların performansı incelenmiştir. Parametrik test olarak, ilk aşamada doğrudan aylık faktör betalarının; ikinci aşamada da hisse senedi getirilerinin ilk aşamada hesaplanmış olan tahmini faktör betalara duyarlılığının hesaplandığı iki adımlı bir yöntem kullanılmıştır. Regresyon sonuçları, likidite azlığı betası ve beklenen hisse senedi getirileri arasında istatistiksel olarak anlamlı pozitif ilişki olduğunu göstermektedir. Sonuçlar; piyasa, defter-piyasa değeri oranı ve momentum faktörleri kontrol edilerek desteklenmiştir. Portföy analizi, yüksek-beta portföyündeki hisse senetlerinin, düşük-beta portföyündekilere oranla yıllık %5 daha fazla kazanç getirdiğini göstermektedir.

Sevgili Annem, Babam ve Kardeşim,

Semra, İshak ve Duygu Günaydın'a

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LIST OF ABBREVIATIONS

CRSP	Center for Research in Security Prices
Nasdaq	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
US	United States
VAR	Vector Autoregression
WLS	Weighted Least Squares

CHAPTER 1

LITERATURE REVIEW ABOUT LIQUIDITY

1.1 Introduction

Liquidity is defined as the ability to trade large quantities easily and without a large effect on price (Pastor and Stambaugh (2003)). Although there are different types of liquidity such as macroeconomic liquidity or funding liquidity, this study investigates the liquidity effects in Turkish stock market. Since there is no accepted definition of asset or market liquidity, liquid markets are generally thought to have some properties. First, small quantities should be traded instantly in liquid markets. Second, large quantities can be sold and bought easily without altering the price. Lastly, in liquid markets, over or underpriced stocks should be traded within a short period of time, but at a premium for buyers and a discount for sellers, which is at the same time positively related to trading volume.

The above definition of liquidity thus combines the time, transaction cost and volume dimensions. Moreover, Kyle (1985) defines liquidity as an elusive concept and explains the three dimensions of liquidity as tightness, depth, and resiliency. Tightness is referred as the difference between the bid and the ask spread. This spread is expected to cover order processing costs, inventory carrying costs and asymmetric information costs. Market depth is referred as the ability to handle the effects of large volume of trades on prices and is measured as the size of the order flow, which is needed for a given amount of price change. Finally, resiliency is defined as a tool to measure how fast the large volumes of uninformed trades dissipation alter the prices. Since it is more burdensome to measure resiliency, investors are more interested in tightness and depth dimensions. Papers studying the liquidity premium typically choose a widely known liquidity measure to test whether the liquidity is indeed priced.

Asset pricing literature treats liquidity as a separate risk factor, thus it needs to be compensated with a liquidity premium. The existence of liquidity premium is investigated by both cross-sectional and time-series concepts. The purpose of this study is to investigate whether illiquidity or illiquidity risk is priced in Turkish stock market using different illiquidity proxies that are prevalent in the literature. In this chapter, a detailed literature review on liquidity measures is presented, and the analysis about liquidity premium is further explained in the subsequent chapters.

1.2 Price-Based Measures

Previous research suggests a role for liquidity in explaining the cross-sectional dispersion in expected stock returns. Since liquidity is not observed directly and it is not possible to capture all aspects of liquidity with a single measure, the empirical literature has put forward a number of liquidity proxies. This section focuses on and introduces liquidity measures which are related to price and return.

Prior to Amihud (2002)'s study, the positive return-illiquidity relationship has been examined across stocks in various studies. In his influential paper, Amihud (2002) examines this relationship over time. The paper documents that there exists a positive link between expected market illiquidity and future equity returns. Amihud (2002) suggests the daily ratio of absolute stock return to dollar volume as a proxy for illiquidity. This measure is linked to the basic description of liquid markets which enables trading with the least impact on price. Defining $|R_{idy}|$ as the return on stock *i* on day *d* and VOL_{idy} is daily volume, Amihud (2002) defines the illiquidity measure as:

$$Illiq_{iy} = 1/D_{iy} \sum_{d=1}^{D_{iy}} \frac{|R_{idy}|}{VOL_{idy}} \tag{1.1}$$

where D_{iy} is the number of days for stock i in year y. This ratio is related to the famous Amivest measure which is the reciprocal of the Amihud measure. (e.g. Cooper et al. (1985)). The Amihud measure has the intuitive interpretation of measuring the average daily association between a unit volume and price change and is based on the concept of response of price to order flow. After calculating $Illiq_{iy}$, Amihud (2002) computes the average market illiquidity across stocks in each year as:

$$Avilliq_y = 1/N_y \sum_{i=1}^{N_y} Illiq_{iy} \tag{1.2}$$

where N_y is the total number of stocks in each year y. In addition to that, $Illiq_{iy}$ needs to be replaced with its mean-adjusted value because average illiquidity varies significantly over the years, as:

$$IlliqMA_{iy} = Illiq_{iy} / Avilliq_y. \tag{1.3}$$

After computing the annual illiquidity measure, Amihud (2002) tests the same hypothesis by using the monthly illiquidity proxy and reaches the same conclusion. Amihud (2002) employs Fama-MacBeth (1973) methodology and documents that expected market illiquidity positively affects ex ante stock returns which at the same time results in future equity excess returns representing an illiquidity premium. Moreover, the study shows that there is a negative correlation between equity returns and contemporaneous unexpected illiquidity. All in all, Amihud illiquidity measure is convenient to be utilized throughout the world markets and this measure has the calculability advantage over others especially in shallow emerging markets.

The applicability of the Amihud measure has been confirmed by many papers in the literature. However, Brennan et al. (2013) claim that asymmetry between stock price changes and order flows can play a significant role in determining equilibrium rates of return. Therefore, their primary goal is to decompose Amihud measure by using other variables that can reflect the sign of the price change and the order flow in order to examine whether those individual elements are also priced. While Amihud measure uses the dollar volume of trading as a proxy for trading activity, Brennan et al. (2013) find it reasonable to re-estimate the illiquidity return premium using an illiquidity measure that is based on turnover as a proxy for trading activity. In order to identify whether buyer and seller initiated trading volumes have different effects on liquidity, the authors decompose individual transactions into buyer-initiated and seller-initiated trades. By doing this, they are able to create a proxy that can capture how large the price moves in response to the trading pressure on one side of the market. Basically, they denote the original Amihud measure as:

$$A^{o} = \frac{|r|}{DVOL} \tag{1.4}$$

where r is daily stock return, and $DVOL$ is daily dollar volume. They argue that since dollar volume is the product of firm size and share turnover, the relative importance of turnover and firm size is not clear. Therefore, the authors decompose Amihud measure into its turnover version and a size-related element as:

$$A^{o} = \frac{|r|}{DVOL} = \frac{|r|}{T}\frac{T}{DVOL} = \frac{|r|}{T}\left(\frac{1}{S}\right)$$
$$= \begin{cases} \frac{r^{+}}{T}\left(\frac{1}{S}\right) = (A^{+})\left(\frac{1}{S}\right), & if\ r \geq 0 \\ \frac{-r^{-}}{T}\left(\frac{1}{S}\right) = (A^{-})\left(\frac{1}{S}\right), & if\ r < 0 \end{cases} \tag{1.5}$$

where T is the daily share turnover (the daily ratio of total number of shares traded to total number of shares outstanding), S is the market value of equity, $A= |r|/T$ is the turnover version of the Amihud measure, r^{+} = max[0,r] and r^{-} = min[r,0]. They also define $A^{+} = r^{+}/T$ and $A^{-} = -r^{-}/T$ and take the natural logarithms of both sides of the above equation (1.5) to explain (1.4) in terms of A and S as:

$$ln(A^{0}) = ln(A) - ln(S). \tag{1.6}$$

The decomposed version of $\ln(A^{o})$ can then be written as:

$$\ln(A^o) = \begin{cases} \ln(A^+) - \ln(S)\,, if\ r \geq 0 \\ \ln(A^-) - \ln(S)\,, if\ r < 0 \end{cases} \tag{1.7}$$

where A^+ and A^- are the half-Amihud measures for up and down days, respectively.

In order to distinguish between the positive and negative return trades, Brennan et al. (2013) decompose share turnover (T) into buyer-initiated turnover (T_B) and seller-initiated turnover (T_S) where $T = T_B + T_S$. By using signed turnover, they thus further decompose the two half-Amihud measures (A^+ and A^-) as:

$$\begin{aligned} A^+ &= \frac{r^+}{T} = \left(\frac{r^+}{T_B}\right)\left(\frac{T_B}{T}\right), && for\ r \geq 0 \\ A^- &= \frac{-r^-}{T} = \left(\frac{-r^-}{T_S}\right)\left(\frac{T_S}{T}\right), && for\ r < 0. \end{aligned} \tag{1.8}$$

After taking logarithm on both sides of these two equations, they get:

$$\begin{aligned} \ln(A^+) &= \ln\left(\frac{r^+}{T}\right) = \ln\left(\frac{r^+}{T_B}\right) + \ln\left(\frac{T_B}{T}\right) = \ln(A_1^+) + \ln(A_2^+) \\ \ln(A^-) &= \ln\left(\frac{-r^-}{T}\right) = \ln\left(\frac{-r^-}{T_S}\right) + \ln\left(\frac{T_S}{T}\right) = \ln(A_1^-) + \ln(A_2^-) \end{aligned} \tag{1.9}$$

where A_1^+ is the directional half-Amihud measure for up days and A_1^- is the directional half-Amihud measure for down days. The two components A_2^+ and A_2^- are the proportions of turnover to buyer- and seller-initiated trades on up and down days, respectively. Moreover, Kyle (1985) suggests an alternative decomposition of the half-Amihud measure, which is the ratio of price changes to net buyer- or seller-initiated trading volume. According to Kyle (1985), two half-Amihud measures can be written as:

$$\begin{aligned} A^+ &= \frac{r^+}{T} = \left(\frac{r^+}{T_B - T_S}\right)\left(\frac{T_B - T_S}{T}\right), && for\ r \geq 0 \\ A^- &= \frac{-r^-}{T} = \left(\frac{-r^-}{T_S - T_B}\right)\left(\frac{T_S - T_B}{T}\right), && for\ r < 0 \end{aligned} \tag{1.10}$$

Taking logarithms on both sides of the above equations yields:

$$\ln(A^{+}) \ = \ \ln\left(\frac{r^{+}}{T_B - T_S}\right) + \ln\left(\frac{T_B - T_S}{T}\right) = \ln(K_1^{+}) + \ln(K_2^{+})$$

$$\ln(A^{-}) \ = \ \ln\left(\frac{-r^{-}}{T_S - T_B}\right) + \ln\left(\frac{T_S - T_B}{T}\right) = \ln(K_1^{-}) + \ln(K_2^{-}) \tag{1.11}$$

where $K_1^{+} = \frac{r^{+}}{T_B - T_S}$ and $K_1^{-} = \frac{-r^{-}}{T_S - T_B}$ are the half-Kyle for up days and half-Kyle for down days, respectively. The two net turnover ratios, $K_2^{+} = \frac{T_B - T_S}{T}$ and $K_2^{-} = \frac{T_S - T_B}{T}$ are the proportional net buyer-initiated turnover on up days and proportional net seller-initiated turnover on down days, respectively.

Following Fama-MacBeth (1973) methodology, Brennan et al. (2013) show that the half-Amihud measure associated with negative-return days is cross-sectionally correlated with equity returns, while the corresponding measure for positive-return days is not statistically significant. Thus, they conclude that only the negative return days are related to return premia. Moreover, when the two half-Amihud measures are decomposed further according to the origin of the trade, the authors find that the magnitudes of the coefficients of buyer- and seller-initiated trades are almost identical; however, the coefficient of seller-initiated trades is statistically significant.

Unlike the developed presence of current liquidity literature claiming that the different illiquidity measures are associated with higher future equity returns, Ben-Rephael et al. (2015) focus on liquidity as a characteristic rather than considering it being a separate risk factor. They propose that the sensitivity of stock returns to liquidity and the liquidity premium have declined over the past half century. In other words, their claim is not about liquidity but they investigate whether the liquidity effect on stock returns has decreased over the years. They use a modified version of Amihud measure as the illiquidity proxy, which is basically adjusted for inflation. Formally, they use the following adjusted measure:

$$Illiq_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{VOLD_{idt} \cdot \inf_{dt}} \tag{1.12}$$

where $\inf_{dt}$ is the inflation adjustment factor, which allows them to present Amihud measure using the end-of-dataset prices. They argue the necessity of such a price adjustment since inflationary effects have changed the meaning of dollar volume over the years. Employing the Fama-MacBeth (1973) approach, they document that the sensitivity of equity returns to liquidity and liquidity premium have declined over the past decades. Moreover, they investigate popular trading strategies, which are based on buying illiquid and selling liquid stocks, and find that the profitability of these trading strategies has lost its significance over this time period. Thus, their main results point out to a decrease in the liquidity premium.

The liquidity of a stock and its variability across time are the key determining factors which attract investors. Thus far, empirical evidence proves that investors prefer more liquid stocks. Some other sensitivity based studies, which will be discussed in detail below, propose that a stock has a lower average return if its liquidity moves inversely with market liquidity. Therefore, in general, how liquidity affects investors leads the way to examine and understand how equity liquidity moves together across stocks, which is also called "commonality" among individual stocks. Moreover, most of the research related to commonality focuses on the U.S. markets. Karolyi et al. (2012) develop a better explanation of both supply- and demand-side commonality across different countries. They aim to explain how and why the level of commonality in liquidity among stocks differs across countries and varies over time. In order to capture the systematic liquidity risk and commonality among stocks, the authors add a constant to the Amihud measure and then take logarithms to reduce the outlier effect. Then, they multiply it with -1 to capture the liquidity, not illiquidity. Thus, they measure liquidity as:

$$Liq_{id} = -\log\left(1 + \frac{|R_{id}|}{VO_{id} \cdot \mathrm{P}_{id}}\right) \tag{1.13}$$

where R_{id} is the return, P_{id} is the price, and VO_{id} is the trading volume of stock *i* on day *d*. After constructing this daily time-series, they compute the monthly time-series for each stock by calculating the equal-weighted average of daily Liq in each month. Moreover, in order to control for general variation in capital market conditions, they also compute the daily turnover ratio as:

$$Turn_{id} = -\log\left(1 + \frac{VO_{id}}{NSH_{iy}}\right) - \frac{1}{N}\sum_{k=1}^{100}\log\left(1 + \frac{VO_{id-k}}{NSH_{iy}}\right) \tag{1.14}$$

where VO_{id} is the trading volume of stock i on day d and NSH_{iy} is the number of shares outstanding at the beginning of year y. Similar to what they do with Liq, they create a monthly time series by calculating the mean turnover ratio in a month for each stock. Their cross-country analysis reveals that even after controlling for country specific determinants, commonality in liquidity is significantly greater in countries with higher average market volatility. Moreover, they show that co-movement in liquidity is greater in countries with more correlated trading activity and in those that have weaker legal protection on investor property rights. Overall, they show that the volatility effect is not symmetric, which then leads to an increase in commonality in liquidity when the market experiences large drops as compared to market boosts.

Another significant research is conducted by Watanabe and Watanabe (2010), which examines the sensitivities of stock returns to liquidity variations in the market. As explained above, market-wide liquidity is a significant factor for the pricing of cross-sectional equities (Karolyi et al. (2012)). However, little is done to understand how this pricing relation can change over time or in other words how the individual stock return sensitivities to aggregate liquidity shocks can vary over time. Watanabe and Watanabe (2010) fill this gap by examining whether liquidity betas change across different states and time. They claim that the variation in uncertainty level across states and time may lead to different liquidity betas and liquidity risk premia. Their claims are based on two frictions in the actual trading environment. First, there exists information asymmetry among investors about their preferences. Second, investors incur trading costs. To test their hypothesis, they first construct an illiquidity measure similar to Amihud (2002) as:

$$PRIM_{jt} = 1/D_{jt}\sum_{d=1}^{D_{jt}}\frac{|r_{jdt}|}{VOL_{jdt}} \tag{1.15}$$

where r_{jdt} and VOL_{jdt} are the return and dollar volume of stock j on day d in month t, respectively and D_{jt} is the total number of daily observations in each month t. Following Amihud (2002), aggregate price impact is calculated as:

$$APRIM_t = \frac{1}{N_t} \sum_{j=1}^{N_t} PRIM_{jt} \tag{1.16}$$

where N_t is the number of stocks in month *t.* Next, they fit an AR (2) model to extract the innovations in liquidity:

$$\left(\frac{mcp_{t-1}}{mcp_1} APRIM_t\right) = \alpha + \beta_1 \left(\frac{mcp_{t-1}}{mcp_1} APRIM_{t-1}\right) + \beta_2 \left(\frac{mcp_{t-1}}{mcp_1} APRIM_{t-2}\right) + \varepsilon_t \tag{1.17}$$

where mcp_{t-1} is the total market capitalization of stocks at month t-1, and mcp_1 is the corresponding value for the initial month in the sample. The ratio $\frac{mcp_{t-1}}{mcp_1}$ helps to control for the time trend in *APRIM.* Lagged and contemporaneous *APRIM* are multiplied by the same factor to capture only the innovations in illiquidity. This adjustment is also utilized by Pastor and Stambaugh (2003). The errors in the above equation are a measure of unexpected illiquidity shocks. Thus, they use the negative of the estimated residuals, $-\widehat{\varepsilon_t}$, as the liquidity measure, LIQ_t. By utilizing the Markov regime switching model, Watanabe and Watanabe (2010) find that liquidity betas change across two different states. The first state is the one with high liquidity betas and the second one is with low liquidity betas. An increase in trading volume predicts a transition from low liquidity-beta state to high liquidity-beta state, which proxies for elevated preference of uncertainty. The high liquidity-beta state shows high volatility and a huge cross-sectional variation in liquidity betas, and it is followed by a decreasing expected market liquidity. Moreover, Watanabe and Watanabe (2010) document that the spread in liquidity betas across the two states is greater for small and illiquid stocks than large and liquid ones, indicating that the sensitivity of liquidity betas of illiquid stocks is higher in an uncertain state.

In addition to those explained price-based measures, some researchers use price to construct a new liquidity measure to proxy for spreads which are directly related to transaction costs. Although the spread based liquidity measures are explained later in detail, it is now sensible to introduce this price-based spread measure. These transaction costs have always been in the focus of financial scholars, since net benefit from an investment is affected by such costs. Trading cost measurements can be very costly and subject to measurement errors. The quoted spread, for example, is only published for a few markets. Roll (1984) presents a method for inferring the effective bid-ask spread directly from a time-series of market prices. The advantage of the method is that it only requires price information to estimate the quoted spread and relies on two major assumptions. The first one is that the asset must be traded in an efficient market. The second assumption is the stationary of the observed price changes. Roll (1984) shows that the covariance between successive price changes can be given as:

$$cov\ (\Delta p_t, \Delta p_{t-1}) = \frac{1}{8}\ (-s^2 - s^2) = -s^2/4 \tag{1.18}$$

which can be simplified as:

$$s_j = 200\ \sqrt{-cov_j} \tag{1.19}$$

where s_j is the spread and cov_j is the serial covariance of returns for asset j and estimated annually from daily and weekly data. Roll (1984) scales this metric by 200 instead of 2 to represent it as percentages. Later, Goyenko et al. (2009) modify this liquidity proxy, since the above formula is undefined when the serial covariance is greater than zero. Thus, they propose the following modified Roll estimator:

$$Roll\ = \begin{cases} 2\sqrt{-\mathrm{Cov}(\Delta p_t, \Delta p_{t-1})}, & \text{When } \mathrm{Cov}(\Delta p_t, \Delta p_{t-1}) < 0 \\ 0, & \text{When } \mathrm{Cov}(\Delta p_t, \Delta p_{t-1}) \geq 0. \end{cases} \tag{1.20}$$

1.3 Volume-Based Measures

Early literature generally uses volume and time related measures to proxy for liquidity. Time is inversely proportional to depth, since as the time to trade a fixed amount of stock decreases, the total trade volume increases. Studies also document a positive relation between liquidity and volume. Traditionally, traded volume has been used as a liquidity proxy. Later, dollar based trading volumes and number of traded contracts began to be used to measure liquidity. Finally, literature came up with the turnover ratio to proxy for liquidity. Turnover gives an idea about how many times the outstanding shares of a stock change hands. In this section, various volume-based liquidity measures are explained and the relative advantages of each measure are discussed.

In asset pricing, future equity returns are cross-sectionally related to the return sensitivities to exogenous factors. Liquidity is one of the important elements for those priced state variables. Chordia et al. (2000) and Lo and Wang (2000) argue that fluctuations in various measures of liquidity covary across assets. It is exactly at this point Pastor and Stambaugh (2003) come into play. They examine whether marketwide liquidity is priced. In other words, they question whether the cross-sectional differences in future equity returns are linked to sensitivities to changes in aggregate liquidity. They argue that their volume-based liquidity measure is more relevant than the other price-based measures for investors who employ some form of leverage. These investors may face margin constraints if their overall wealth plummets and thus, they must raise cash by liquidating some assets. If they hold assets with high sensitivities to liquidity, then such mandatory liquidations will be much more frequent when illiquidity is higher, since decrease in wealth is significantly positively correlated with decrease in liquidity. Therefore, liquidity is costlier when it is lower, and investors hence prefer assets which are less likely to be required liquidation when illiquidity is high.

Pastor and Stambaugh (2003) concentrate on an aspect of liquidity that is associated with temporary price fluctuations induced by order flow. Their liquidity measure is the ordinary least square estimate of $\gamma_{i,t}$ in the regression:

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t}\, r_{i,d,t} + \gamma_{i,t}\, \mathrm{sign}(r^e_{i,d,t}) \,.\, v_{i,d,t} + \varepsilon_{i,d+1,t} \quad d=1,\ldots\ldots,D, \qquad (1.21)$$

where $r_{i,d,t}$ is the return of stock *i* on day *d* in month *t*, $r^e_{i,d,t} = r_{i,d,t} - r_{m,d,t}$, where $r_{m,d,t}$ is the return on the CRSP value-weighted market return on day *d* in month *t*, and $v_{i,d,t}$ is the dollar volume for stock *i* on day *d* in month *t*. The basic idea in the regression is that, if signed volume is viewed as "order flow", then higher illiquidity is reflected in a greater tendency for order flow in a given direction on day *d* to be followed by a price change in the opposite direction on day *d*+1. Higher illiquidity then corresponds to stronger volume-related return reversals. Thus, they expect $\gamma_{i,t}$ to be negative and to increase in absolute terms as illiquidity increases. Later, the market wide liquidity measure is calculated as:

$$\widehat{\gamma_t} = \frac{1}{N} \sum_{i=1}^{N} \widehat{\gamma_{i,t}} \tag{1.22}$$

where N is the number of stocks in each month. Since the dollar volume changes its value across time, it is not surprising to see that the raw values of $\widehat{\gamma}_t$ are smaller in magnitude later in the sample. Therefore, Pastor and Stambaugh (2003) compute the series $(m_t/m_1)\,\widehat{\gamma}_t$, where m_t is the total dollar value of all stocks at the end of month t-1. They calculate the innovations in aggregate liquidity using the formula:

$$\Delta\widehat{\gamma}_t = \left(\frac{m_t}{m_1}\right) \frac{1}{N_t} \sum_{i=1}^{N_t} \left(\widehat{\gamma_{i,t}} - \widehat{\gamma_{i,t-1}} \right) \tag{1.23}$$

where N_t is the number of stocks having data in both the current and previous month. They later regress $\Delta\widehat{\gamma}_t$ on its lag as well as the lagged value of the scaled series as:

$$\Delta\widehat{\gamma}_t = a + b\,\Delta\widehat{\gamma_{t-1}} + c\left(\frac{m_{t-1}}{m_1}\right)\widehat{\gamma_{t-1}} + u_t\ . \tag{1.24}$$

The innovation in liquidity, L_t, is calculated as the fitted residual divided by 100:

$$L_t = \frac{1}{100}\,\widehat{u_t}. \tag{1.25}$$

After constructing this liquidity measure, by following a two stage procedure, Pastor and Stambaugh (2003) use it as a pricing factor and conduct portfolio analysis. They find that future equity returns are cross-sectionally related to the sensitivities of equity returns to innovations in aggregate liquidity. They add that equities which have a high sensitivity to aggregate liquidity have higher future returns. Moreover, according to their liquidity measure, smaller stocks tend to be illiquid, and the smallest stocks are more sensitive to aggregate liquidity as compared to the largest stocks. They also show that their four-factor model (Fama-French 3 factors and a liquidity factor) seems to explain the momentum anomaly.

Investors care about expected returns net of trading costs, thus they expect less liquid assets to provide higher gross returns compared to more liquid assets. Amihud and Mendelson (1986) formalize the important relation between market microstructure and asset prices, and show that asset returns are positively correlated to transaction costs. In contrary, Eleswarapu and Reinganum (1993) use the same proxy as Amihud and Mendelson (1986) and find that the month of January elevates the covariation between bid-ask spread and stock returns. Later, in contrast to the result of Eleswarapu and Reinganum (1993), Brenan and Subrahmanyam (1996) do not find any evidence of seasonality in liquidity premium.

Datar et al. (1998) examine the relationship between liquidity and asset returns by using a different market microstructure variable: turnover ratio. They suggest turnover rate of a stock as a proxy for liquidity and define it as the number of shares traded divided by the number of shares outstanding for that specific stock. They advocate using turnover rate for two reasons. First, they claim that turnover rate has strong theoretical roots and Amihud and Mendelson (1986) prove that liquidity is correlated with trading frequency. The second reason is the ease of calculating turnover rate from the available data. Datar et al. (1998) aim to find whether stock returns are negatively correlated with liquidity. Using the methodology of Litzenberger and Ramaswamy (1979), which is a refinement of the Fama-Macbeth (1973) methodology, Datar et al. (1998) find that stock returns are negatively correlated with turnover rates. This result confirms the claim that illiquid stocks provide higher average returns. Unlike the findings of Eleswarapu and Reinganum (1993), Datar et al. (1998) find evidence that liquidity effect is not restricted to January. Indeed, they show that turnover rates are related strongly to stock returns throughout the year after controlling for size, book-to-market ratio and beta of the stock.

1.4 Transaction Cost Measures

Bid-ask spreads can be considered as a mark-up price paid to provide immediate and faster transactions in the market. Both parties, sellers or buyers, cannot be sure whether there is going to be a prevailing price that they will both agree on. Additionally, the time to trade depends on prevailing conditions of the stock and the microstructure of the market. If each one of those parties does not want to wait, then they can immediately trade with the market makers who stand on hold to transact by incurring a transaction cost. These incurred transaction costs heavily depend on the liquidity of the market and the stock that is being traded. Therefore, bid-ask spread and the liquidity of the underlying asset are negatively correlated.

In the literature, alternative ways of defining the bid-ask spread have been used. The quoted spread is defined as the difference between bid and ask prices at which the individual market maker is willing to trade. On the other hand, the inside spread is the difference between the highest bid and the lowest ask price being quoted by any market maker in a security. The quoted spread is calculated as:

$$quoted_d^i = a_d^i - b_d^i \tag{1.26}$$

where a_d^i is the lowest ask price and b_d^i is the highest bid price for stock *i*. These bid and ask prices are the closing prices on that day. The second type of spread is the relative spread and it is computed as:

$$rquoted_d^i = \frac{\left(a_d^i - b_d^i\right)}{m_d^i} * 100 \tag{1.27}$$

where m_d^i is the mid-point of the best bid and ask prices, i.e. $m_d^i = \left(a_d^i + b_d^i\right) / 2$. Similarly, the effective spread is calculated as:

$$effective_d^i = 2 * \left|p_d^i - m_d^i\right| \tag{1.28}$$

where p_d^i is the closing price of stock *i*.

Eleswarapu (1997) examines the relation between transaction costs and expected returns using only Nasdaq stocks. Eleswarapu (1997) concentrates only on the Nasdaq stock market data for four reasons. First, there are differences in the accuracy of the transaction cost measurement between Nasdaq and NYSE stocks due to their differences in market structure, and the inside quotes on the Nasdaq seem to be a better proxy for the actual transaction cost. Secondly, there exists a larger variance in the spreads of Nasdaq stocks as compared to NYSE stocks, thus Nasdaq data enables to test the hypothesized relation easily. Thirdly, Eleswarapu (1997) mentions that the liquidity premium on the Nasdaq has some policy implications for the companies. Lastly, the author uses the daily spreads for Nasdaq stocks to capture the variation of the spread for a specific stock within each year, however earlier studies use NYSE data in which bid and ask spreads for a stock are measured by taking the average of the spreads corresponding to the beginning and end day of the year. The primary liquidity measure that Eleswarapu (1997) uses is the relative bid-ask spread. Following the Fama and MacBeth (1973) methodology, the author finds that stocks with larger spreads yield higher average returns. Moreover, unlike the findings of Eleswarapu and Reinganum (1993), which show that liquidity is not priced in the non-January months using a sample of NYSE stocks, Eleswarapu (1997) finds that although the spread effect is stronger in January, liquidity is also priced in the non-January months.

The existing literature mostly investigates the relation between return and liquidity in the U.S., which is a large and hybrid-driven market and finds a negative link between stock return and liquidity. However, little is known about this relationship in small and pure order-driven markets. Constructing a new liquidity measure, Marshall (2006) aims to fill this gap by investigating the return-liquidity relationship on the pure-order driven Australian Stock Exchange. Although order based measures, such as the bid-ask spread, are efficient liquidity measures for small investors and since these investors most of the time complete their orders at the bid and ask price, larger investors may not always trade at these prices. Therefore, bid-ask spread may underestimate the true cost of trading for these investors. Marshall (2006) examines whether a new liquidity measure, Weighted Order Value (WOV), can explain the relationship between return and liquidity in a small and pure order-driven market. The hypothesis is that returns are negatively correlated with liquidity. The bid execution rate is calculated as:

$$Bid\ Execution\ Rate = \frac{Number\ of\ Orders\ Executed\ in\ Each\ Bid\ Price\ Band}{Total\ Number\ of\ Orders\ in\ Each\ Bid\ Price\ Band}. \qquad (1.29)$$

This ratio is calculated at the end of each half-hour interval. Then, the Bid Order Value for each price band is calculated by multiplying the bid prices by the bid order volumes for each price, as:

$$Bid\ Order\ Value = \sum(Bid\ Price\ \times Bid\ Volume) \tag{1.30}$$

The Weighted Bid Value is then calculated as:

$$Weighted\ Bid\ Value = \sum(Bid\ Order\ Value\ \times Bid\ Execution\ Rate) \tag{1.31}$$

This same procedure is repeated for ask orders as well. Weighted Order Value (WOV) is finally computed as:

$$WOV = \sqrt{Weighted\ Bid\ Value\ \times\ Weighted\ Ask\ Value}\ . \tag{1.32}$$

Marshall (2006) underlines the advantages of WOV in terms of covering both bid-ask spreads and market depth, which is not the case for traditional liquidity proxies. In other words, the author mentions that compared to other trade based measures, WOV covers orders that are available for an investor to trade against and at the same time it incorporates depth which is available at each quote. Using the standard Fama and MacBeth (1973) methodology for cross-sectional analysis, Marshall (2006) finds the coefficient of WOV to be negative and statistically significant. Since WOV is positively correlated with liquidity, the negative relation between return and WOV suggests a positive liquidity premium. Given the existence of inconclusive papers on the liquidity premium in pure order-driven markets by using the traditional liquidity measures such as bid-ask spread, Marshall (2006)'s finding of positive liquidity premium proves the superiority of WOV to bid-ask spread and turnover rate in those markets. Moreover, unlike the finding of Eleswarapu and Reinganium (1993), this positive liquidity premium exists throughout the year.

Although all market participants are aware of the significant feature of liquidity and trading activity in financial markets, relatively little is known about their time-serial properties. Up to Chordia et al. (2001)'s paper on market liquidity and trading activity, existing research about trading costs has been conducted using short-time spanning data. In addition to this, those studies have mostly investigated the liquidity of individual stocks. This is mainly due to the tedious task of handling such enormous data. Moreover, those previous studies such as Chordia et al. (2000) and Hasbrouck and Seppi (2001) study the commonality in the time-series movement of liquidity, but they do not analyze the behavior of aggregate market liquidity over time. Therefore, Chordia et al. (2001) contribute to the literature by analyzing aggregate market spreads, depths, trading activities for U.S. stocks and time-series behavior of liquidity with macroeconomic variables over an extended period of time. Using intra-day data and dealing with approximately 3.5 billion transactions from the equity markets, they utilize quoted spread and depth as liquidity measures. They show that the daily changes in market averages of liquidity and trading activity are highly volatile and negatively serially dependent, and that liquidity significantly decreases in down markets. They also document that recent volatility that appears in the market induces a drop in trading activity and spreads. Moreover, they prove the existence of a strong day-of-the-week effect. Specifically, trading activity and liquidity significantly drop on Fridays, whereas they increase on Tuesdays. Finally, the authors show that depth and trading activity increase just before major macroeconomic announcements.

Not long after their previous paper, Chordia et al. (2002) discuss the joint relation among trading activity, liquidity and stock market returns using high frequency data. Most of the studies up to this time use volume as a proxy for trading activity; however, volume alone does not give much idea about trading. They support this point by using a trade of one thousand shares as an example. At one extreme, this can be a thousand shares sold to the market maker and at the other extreme, this can be a thousand shares purchased. For each implementation, the liquidity will be different. Therefore, order imbalance can be seen as a more important variable than volume for the liquidity-return relationship. Previously, most researchers examine order imbalances around specific dates or over shorter time periods. Chordia et al. (2002) contribute to the debate by constructing an estimated marketwide order imbalance for NYSE stocks and investigate: i) properties and determinants of marketwide daily order imbalance, ii) the relation between order imbalance and aggregate liquidity, and iii) the relation between daily stock market returns and order imbalance after controlling for aggregate liquidity. Their paper is thus the first study to use the daily order imbalance for a large sample of equities over an extended time period. The authors use the aggregate daily order imbalance, buy orders less sell orders, as a proxy for liquidity, and define the following algorithm to identify whether a trade is seller- or buyer-initiated. They classify a trade buyer- (seller-) initiated if it is closer to the ask (bid) of the prevailing quote, and create the following daily order imbalance variables:

- $OIBNUM_t$: the number of buyer-initiated trades less the number of seller-initiated trades on day *t*,
- $OIBSH_t$: the buyer-initiated shares purchased less the seller-initiated shares sold on day *t*,
- $OIBDOL_t$: the buyer-initiated dollars paid less the seller-initiated dollars received on day *t*,
- $QSPR_t$: the quoted bid–ask spread averaged across all trades on day *t*.

Using the above variables to proxy for the order imbalance and liquidity, Chordia et al. (2002) come up with the following results. First, they find a strong evidence that order imbalance is related to past market returns. They show that signed order imbalances are high after market drops and low after market rises. Second, they document that liquidity is predictable not from past order imbalances, but from market returns. Third, they prove that large-negative-return days can be predicted by order imbalances and returns. Lastly, they provide support for a strong relationship between order imbalance and contemporaneous absolute returns after controlling for market volume and aggregate liquidity.

In spite of the fact that majority of papers in the literature use bid-ask spread as the liquidity proxy, it is a noisy measure, because many high volume transactions take place outside the spread and many low volume transactions take place within the spread. Therefore, apart from using the quoted spread as the liquidity measure to study liquidity-return relation, it is wise to investigate whether illiquidity due to information asymmetry affects expected stock returns. Brennan and Subrahmanyam (1996) examine the importance of adverse selection measures in driving asset returns. To achieve that goal, they estimate the illiquidity measure from intraday transaction data and use two different methods to decompose estimated trading costs into variable and fixed components. They define fixed cost as a trading cost which is a constant proportion of the transaction value, and variable cost as a trading cost which varies with the value of the transaction. They estimate fixed and variable components of trading costs, denoted by Ψ and λ, respectively by utilizing the following two different empirical models for price formation:

i) Glosten-Harris Model:

Brennan and Subrahmanyam (1996) denote m_t as the expected value of the stock at time *t*, for a market maker who only knows the order flow, q_t, and a public information signal, y_t. Kyle (1985) implies that m_t will evolve according to:

$$m_t = m_{t-1} + \lambda q_t + y_t \tag{1.33}$$

where λ is the (inverse) market depth parameter. Next, they let D_t be the sign of the incoming order at time *t*. They assign +1 for buyer-initiated trades and -1 for seller-initiated trades. Given this order sign D_t, and denoting the fixed cost component by Ψ, they express the transaction price, p_t, as:

$$p_t = m_t + \Psi D_t. \tag{1.34}$$

Substituting m_t from the equation (1.33) to equation (1.34) yields:

$$p_t = m_{t-1} + \lambda q_t + \Psi D_t + y_t. \tag{1.35}$$

Since $p_{t-1} = m_{t-1} + \Psi D_{t-1}$, the price change, Δp_t, can be explained as:

$$\Delta p_t = \lambda q_t + \Psi[D_t - D_{t-1}] + y_t \tag{1.36}$$

The authors use this last equation to estimate the *Glosten-Harris* λ.

ii) The Hasbrouck-Foster-Viswanathan model:

This model utilizes the price response to unexpected volume as the measure of the adverse selection component of the price change. The basic idea is that if trades can be predicted from past price changes, then part of the order flow is predictable, and thus should not be included to measure the information content of a trade. They let Δp_t be the transaction price change for transaction *t*, q_t be the signed trade quantity corresponding to the price change, and D_t be the direction of trade. Later, they consider the following model with five lags for the estimation:

$$q_t = \alpha_q + \sum_{j=1}^{5} \beta_j \, \Delta p_{t-j} + \sum_{j=1}^{5} \gamma_j \, q_{t-j} + \tau_t \tag{1.37}$$

$$\Delta p_t = \alpha_q + \Psi \, [D_t - D_{t-1}] + \lambda\tau_t + \nu_t. \tag{1.38}$$

Brennan and Subrahmanyam (1996) measure the informativeness of trades by the coefficient of τ_t, the residual from the first equation. To test their hypothesis, they first estimate the intercepts from the time-series regression of the excess returns on the λ-sorted portfolios on the Fama-French factors. After rejecting the null hypothesis that these intercepts are jointly zero, they perform generalized least squares (GLS) of the portfolio returns on measures of trading costs and the Fama-French factors to examine the relation between the portfolio returns and market illiquidity. As a result of this analysis, they find a significant return premium associated with both the fixed and variable cost of transacting elements. They also document an additional risk premium associated with an inverse price factor after risk adjustment using Fama-French three factor model. Lastly, they show that there exists no seasonality effect in the premiums unlike the result of Eleswarapu (1997).

So far, I have introduced many alternative measures of liquidity and discussed the underlying ideas and assumptions behind them. Each one of these measures has systematic and individual components. Korajczyk and Sadka (2008) combine information from different liquidity measures to construct a common element of asset liquidity. They contribute to the literature in various ways. First, the authors test whether the different measures of liquidity risk factor are cross-sectionally priced. Secondly, after controlling for across-measure systematic risk, they investigate whether there exists evidence for an independent pricing of systematic liquidity risk for different liquidity measures. Lastly, even after controlling for liquidity risk, they check whether any of the liquidity characteristics are priced. They use the Amihud measure, as in Eq. (1.1), turnover ratio, quoted and effective spreads and four price impact measures. The authors run regressions of transaction prices on trading metrics to calculate the price impact proxies. In addition to these measures, the authors use a time-series of monthly order imbalance and strengthen the existence of stock commonality across different measures of liquidity. Return shocks are also found to be correlated with liquidity shocks, and can be used to predict liquidity. They also find that aggregate systematic liquidity is indeed significantly priced.

In the empirical asset pricing literature on liquidity, the idea that market declines lead to a decrease in asset liquidity, has been gaining popularity recently. These liquidity drops occur when stock holders sell in panic, and financial intermediaries refrain from increasing the liquidity. Hameed et al. (2010) investigate the reaction of market liquidity following larger market drops, and test whether financial intermediaries refrain from providing enough liquidity. In theory, there are several ways to obtain liquidity after market declines. Market makers know temporary liquidity shocks and they also know the funding constraints. Therefore, when stock prices drop sharply, those intermediaries hit their margin constraints and are then obliged to liquidate their assets. As Brunnnermeier and Pedersen (2009) show, such a large market shock leads to high illiquidity and high margin equilibrium, which further increases margin requirements. This illiquidity loop thus avoids dealers from providing market liquidity. The authors use the relative spread in Eq. (1.27) as the liquidity proxy. However, they argue that since spreads have narrowed down recently with a decrease in tick size, they need to be adjusted for changes in tick size, time trend and calendar effect. To achieve that goal, Hameed et al. (2010) regress the relative quoted spread for each stock on various variables that are known to capture the seasonality effect of liquidity. After the analysis, Hameed et al. (2010) document that the decrease in liquidity as a result of a market decline is much more than the increase in liquidity as a result of a market increase, and this effect is stronger for highly volatile firms. After large negative market returns, they document an increase in commonality in liquidity, and show that commonality boosts when liquidity crises emerge. Moreover, they prove the existence of illiquidity contagion across industries, and show that commonality in liquidity within an industry increases when returns on other industries are negative and large in absolute value.

I have so far explained the studies which introduce unique liquidity measures to the literature. Now, it is time to turn our attention to their comparisons, and their validity in different markets. In the last decade, emerging markets experienced high growth rates and the increasing investment needs in emerging markets resulted in significant returns. However, there is a risk attached to these high returns and thus, those returns have dropped significantly due to the lack of liquidity of stocks in those countries. Although risk, return and volatility have been analyzed in the literature, liquidity has not yet been covered in detail for emerging markets. Lesmond (2005) fills this gap by testing different liquidity measures by using both cross-country and within-country analysis for emerging markets. The author introduces the new LOT measure and compares it with other widely known liquidity proxies. The LOT measure is basically a combination of spread, transaction and price impact costs. Lesmond (2005) finds that the LOT or Roll measure are good at explaining the liquidity differences between countries. However, the author reports that for countries that have high illiquidity levels, Amihud and turnover measures are downward biased, and finds that the LOT and Amihud measures are superior than the Roll and turnover measures for within-country analysis. Lesmond (2005) also shows that countries with weak legal institutions have higher liquidity costs than do those with strong legal institutions.

Similar to Lesmond (2005), Bekaert et al. (2007) concentrate on emerging countries where the effect of liquidity is strong and argue that if liquidity premium is important for those markets, then those markets should yield powerful tests and evidences. They focus on emerging markets; however, the transaction data, such as bid-ask spread or intra-day data, are not available for these markets. To overcome this data problem, Bekaert et al. (2007) utilize illiquidity proxies which depend upon the occurrence of zero daily returns. This proxy is originally suggested by Lesmond et al. (1999) and Lesmond (2005). Lesmond (2005) advocates this measure by claiming that if the value of an information signal is not high enough to balance the costs, then market makers will not trade, which leads to a zero return. This measure requires only a time-series of daily returns which is indeed a significant advantage. Since, the longer periods of consecutive non-trading days correspond to higher illiquidity, the authors use a modified version of the zeros measure to get rid of the stale prices. They call this measure the daily "price pressure". They later estimate VAR systems to test their hypothesis for emerging countries. They find that zeros measure is associated with expected equity returns and returns are positively correlated with unexpected illiquidity shocks. They also compare the markets in terms of their liberalization, and study various models that allow for liquidity risk depending on whether a country is integrated, and find that local systematic risk is more important than local market risk. The authors conclude their study by mentioning that poor law conditions and high political risks are significant indicators, and liquidity occupies a larger role in future returns in countries with such conditions.

Various studies in the literature proxy for liquidity and transaction costs by using daily return and volume data. These studies investigate whether stock returns have any relationship with the liquidity measure. However, by doing this analysis, they mostly ignore whether the liquidity measures are indeed associated with the actual transaction costs. The underlying assumption to test all these hypothesis is that liquidity proxies capture the transaction cost of the market. Indeed, due to the limited availability of actual trading costs, this assumption is not tested in the first place. Given the limited number of liquidity proxies tested in the literature, there are still differing views regarding the quality of each measure and the literature did not arrive at a consensus whether these proxies truly capture the transaction costs. Goyenko et al. (2009) aim to address this point by examining different liquidity measures. They test all these widely used proxies for liquidity to decide which one is better in terms of its ability to proxy for the actual transaction costs. The authors introduce a modified version of the original Roll measure, which is the ratio of the Roll measure to the average daily dollar volume and a modified zeros measure, which is the proportion of positive-volume days with zero return to number of trading days in each month. Using these proxies along with the others, the authors find effective tick to be the best measure in terms of the ease of computation. They also show that prevalent measures in the literature such as the Amihud, Pastor and Stambaugh and Amivest measures are not pertinent proxies for the spreads. The authors also find that it is more difficult to capture the price impact in the data than the effective or realized spread, and the measures are not good at capturing the high frequency price impacts. Moreover, they document that Pastor and Stambaugh and Amivest measures are not efficient in calculating the price impact. If researchers want to capture price impact, they should utilize the Amihud measure or one of the effective spread proxies divided by volume. Thus, Goyenko et al. (2009) conclude that despite the fact that the Amihud measure is good at measuring the price impact, effective or realize spread measures come first in the horserace.

Thanks to the increased influx of foreign direct investments to emerging markets, the stock market of these countries grew rapidly in the last decade. Investors in these markets are attracted by high returns while facing high illiquidity risks. Emerging markets also have more insider trading and lower average surplus compared to the U.S. All these factors lead to low average trading activity in emerging markets. Besides, the trading activity varies significantly across countries. As a consequence, the performance and validity of some liquidity proxies may differ across individual markets. For instance, the zeros measure becomes close to zero for active markets, whereas those values significantly deviate from zero for less-active markets. Kang and Zhang (2014) thus propose a new liquidity measure to take this effect into account. Their measure incorporates the price impact and the trading frequency. The authors aim to conduct a comparison analysis among prevalent liquidity proxies in the literature and introduce the new liquidity measure, which is calculated as:

$$Illiqzero_{\ it} = \left[ln\left(\frac{1}{N_{it}}\sum_{t=1}^{N_{it}}\frac{|R_{it}|}{VOL_{it}}\right)\right] \times (1 + NT\%_{it}) \tag{1.39}$$

where N_{it} is the number of non-zero trading volume days for each stock within each month, and $NT\%$ is the percentage of non-trading days in each month. This new illiquidity proxy can be considered as the non-trading-day adjusted version of the Amihud measure. As a result of the analysis, the authors find *Illiqzero* to be the best-low frequency illiquidity proxy. This result shows the applicability and the validity of this new measure in emerging markets. Moreover, they show that *Illiqzero* captures the variations that cannot be otherwise captured by the linear combinations of all other illiquidity proxies. Finally, as a result of the cross-sectional analysis using *Illiqzero* and high-frequency liquidity proxies, the authors find that liquidity is lower for small and high volatile stocks, yet this is not the case if other liquidity proxies are used.

As already covered by various papers, there are two different ways that liquidity can affect the asset returns. The first way is that liquidity is a characteristics of the asset returns.

Secondly, liquidity can be thought as a separate risk factor. Acharya and Pedersen (2005) thus propose a liquidity-adjusted capital asset pricing model (LCAPM) which covers three different aspects of liquidity risk. Moreover, thus far in the studies of world market liquidity, researchers have either focused on the liquidity levels (Lesmond (2005)), or have been more interested in the systematic aspects of liquidity. (Bekaert et al. (2007); Karolyi et al. (2009)). Karolyi et al. (2009) are interested in the commonality in liquidity in global markets and Bekaert et al. (2007) examine the different forms of liquidity risk of the emerging markets. Lee (2011) contributes to the literature by examining an equilibrium asset pricing relation. The author considers liquidity both as a characteristics and as a separate risk factor. To achieve this goal, Lee (2011) investigates whether the validity of LCAPM in the U.S. is also prevalent in global markets. The author employs a cross-sectional regression framework and a factor model regression to examine this issue and also investigates whether the U.S. market has a crucial role in the pricing of global liquidity risk. Lastly, Lee (2011) examines the differences, and the sources of those differences of the local and global liquidity risk in asset pricing. The author employs the zeros measure as the liquidity proxy. Following the Fama and MacBeth (1973) methodology to perform cross-sectional regressions, consistent with the LCAPM, the author finds that liquidity risk is priced in international financial markets. Especially, after controlling for market risk, liquidity level, size, and book-to-market, the author shows that an asset's rate of return depends on the covariance of its own liquidity with the aggregated liquidity at that country's market, and covariance of its own liquidity with local and global returns. Lee (2011) also shows that global liquidity risk is a priced factor. This result explains the important role of the U.S. market in the world. Moreover, the author shows that the significance of global liquidity risk is higher than that of local liquidity risk in countries which are more open and have low political risk. However, Lee (2011) documents that local liquidity risk is more pronounced than global liquidity risk for countries which have less global investors.

So far, various papers which show the existence of a strong relationship between stock return and illiquidity have been covered. The vast majority of the literature agrees now that illiquidity is associated with a positive return premium. However, there is also a literature on the effects of microstructure-induced noise for empirical finance applications. The effect of this noise-related bias on the relationship between liquidity and stock returns has not been fully understood. Therefore, Asparouhova et al. (2010) focus on the potential biases in the tests which examine whether liquidity is a priced risk factor. They suggest several methodological corrections for those biases which arise as a result of micro-structural noise, and show that the biases can be eliminated by a procedure where each return is weighted by the observed gross return on the same security in the prior period. Asparouhova et al. (2010) claim that sensitivity of expected stock returns to different measures of liquidity and the liquidity premium is biased towards finding a premium. They investigate this issue by using an array of illiquidity measures that are prevalent in the literature. Implementing the correction methods, the authors show that estimated premiums for illiquidity are significantly upward biased. They point out that those microstructure noises in security prices bias the results of empirical asset pricing specifications, and the microstructure noise attributable biases can be eliminated by running WLS regressions to estimate the return premiums that rely on stock returns as the dependent variable, and the prior-period gross return as the weighting variable. However, after correcting for the upward bias, they show that there still exists a strong evidence of a positive return premium for all of the measures used. Moreover, as a result of the simulation analysis, they document that upward biases in the estimated spread premiums can be reduced by excluding outlier securities. However, doing this has a negative effect in terms of statistical power such that the researcher may not be able to find the correct illiquidity premium.

I have thus far focused on the international articles which are mostly originated in U.S. Since I am interested in the liquidity in Turkish markets, it is now time to turn the attention to researches that study the liquidity premium in Turkish markets. Yuksel, Yuksel, Doganay (2010) investigate whether liquidity premium exists in Borsa Istanbul. They aim to prove the existence of a strong liquidity premium in Turkey. As a liquidity measure, they use the asset's turnover ratio, and to perform the cross-sectional analysis, they use the standard Fama and MacBeth (1973) procedure and control in their regression for liquidity measure, beta, size and book-to-market equity. The second methodology they implement takes liquidity as a separate risk factor, and checks whether this new liquidity factor is a priced source of risk in a Fama and French (1993) framework. As a result of their analysis, they find that liquidity and book-to-market equity ratio seem to explain the variation of expected returns. Moreover, using the GRS (1989) test statistics, they show that although the Fama and French (1993) three factor model is not sufficient to explain the correct fitted model, the four factor model, that is Fama and French (1993) three factor model plus a liquidity factor, fits the data correctly.

As it is easily seen, the effect of liquidity has not yet been fully investigated in Turkish markets. Yuksel et al. (2010) try to explain liquidity premium by using only the turnover ratio. However, more detailed research needs to be conducted using different liquidity measures and controlling for different cross-sectional determinants. In subsequent chapters, I aim to fill this gap by examining the liquidity in Turkish markets with greater detail and by using different liquidity measures, and investigate whether liquidity premium exists in Turkish markets.

CHAPTER 2

LIQUIDITY AND EQUITY RETURNS IN BORSA ISTANBUL

2.1 Introduction

Liquidity, defined as the ability to trade large quantities at ease, at a low cost and without a large price impact, has been argued to be a broad and elusive concept (Pastor and Stambaugh (2003)). Many researchers have attempted to measure liquidity and investigated the existence of an illiquidity premium. Theory suggests that investors require higher returns on assets with lower liquidity to compensate themselves for the higher cost of trading these assets, i.e., the higher an asset's liquidity, the lower its expected return. In their seminal paper, Amihud and Mendelson (1986) assert liquidity as a factor that co-varies with stock returns. Amihud (2002) shows that liquidity predicts future returns and liquidity shocks have a positive correlation with return shocks. Although there is an abundance of studies that examine the liquidity-return relation in U.S. markets, relatively little research has been conducted in non-U.S. markets. With the tenfold increase in foreign direct investments in Turkey during the past decade and a share turnover velocity that ranks third in the world, Borsa Istanbul is a particularly appealing setting to study the existence of an illiquidity premium.[1]

The findings related to the trade-off between liquidity and returns for non-U.S. studies are mixed and I aim to contribute to the debate by providing new evidence on this issue. Turkey has been in the spotlight for international investors as it has been further integrated

[1] Foreign direct investments have increased from $1.1 billion to $12.5 billion since 2002 according to the Investment Support and Promotion Agency of Turkey. Borsa Istanbul ranks third in the world with a monthly share turnover velocity of 223% at the end of 2014 according to the World Federation of Exchanges.

with the global economy in recent years.[2] Borsa Istanbul is the largest equity market in terms of market capitalization in Central and Eastern Europe (CEE). During the past decade, Turkey has been one of the leading emerging countries that attracted foreign investment flows. Turkey's gross domestic product (GDP) per capita has increased almost fourfold and the number of stocks listed in the Turkish stock market has almost doubled over the period from 2002 to 2014. Annual interest rates have fallen from 65% to 7% and inflation has been kept under control. Increased foreign direct investments and record-level share turnover velocity highlight an active security market in Turkey that attracts international interest. These economic developments about Turkey and the fact that international investors give a great importance to the ease of liquidating their investments in an emerging market at a fair value when they wish to, make the examination of the illiquidity premium in this market essential.

While studying the role of liquidity, I pay attention to the issue pointed by Subrahmanyam (2010) regarding the robustness of research results to the use of different liquidity metrics. Goyenko et al. (2009) also argue that the performance of various measures in capturing liquidity may differ using international data. Keeping these issues in mind, I gather a wide range of illiquidity proxies that can be applied to the Turkish market to capture multiple dimensions of liquidity risk.

My results document that liquidity plays an important role in explaining stock returns in Borsa Istanbul. Following Fama-MacBeth (1973), separate cross-sectional regressions are estimated for each month where the dependent variable is one- to six-month ahead equity returns and the independent variables are various illiquidity measures. Cross-sectional regressions indicate a positive and significant relation between the illiquidity measures and expected stock returns. For the univariate regression specification with one-month horizon, the t-statistics for the illiquidity measures vary between 1.95 and 3.81. This positive return-illiquidity relation is robust to the presence of common firm-specific characteristics such as market beta, size, book-to-market and momentum in the regression specification. Moreover, the portfolio analysis indicates that stocks that belong to the highest illiquidity quintile earn 7.2% to 19.2% higher monthly future returns compared to stocks in the lowest illiquidity

[2] See Akdeniz et al. (2000), Akdeniz et al. (2013), Atilgan et al. (2015) and Imisiker and Tas (2013) for studies that investigate other determinants of equity returns in Borsa Istanbul. Bali et al. (2013) and Cakici et al. (2013) extend this line of research to the international setting.

quintile. I show that these return differences cannot be explained by popular asset pricing factors such value, size and momentum. Dependent double sorts based on the firm size or return volatility and illiquidity reveal that the illiquidity premium manifests itself more strongly for small stocks and stocks with high volatility. Additionally, I calculate the transition probabilities of stocks from one illiquidity quintile to another in future periods and show that illiquidity is a persistent equity characteristic. Finally, I find that the illiquidity premium increases (decreases) during periods of extremely low (high) market returns.

The structure of the paper is as follows. Section 2 reviews the literature on liquidity. Section 3 describes the data and the methodology. Section 4 presents the empirical findings. Section 5 concludes.

2.2 Literature Review

The empirical literature has suggested a number of liquidity proxies. Earlier studies examine the cross-sectional relation between return and liquidity using transaction-cost based proxies such as the bid and ask spread. This spread can be considered as a mark-up price that needs to be paid to provide faster transactions. Amihud and Mendelson (1986) find that equity returns increase with the bid-ask spread. Eleswarapu (1997) tests the Amihud and Mendelson (1986) model using only Nasdaq stocks and also finds a strong support for the significant relationship between spread and average returns. Up to Chordia et al. (2001), the literature on trading costs focuses mostly on short time horizons. Instead, Chordia et al. (2001) analyze market spread, depth and trading activity for U.S. equities over an extended period of time and find a strong negative relationship between liquidity and stock returns, complementing the earlier studies. More recently, Bali et al. (2014) document that liquidity shocks are positively correlated with contemporaneous stock returns and also predict future price movements.

In addition to the studies that investigate the return-liquidity relation across stocks, Amihud (2002) utilizes a time-series approach. Amihud (2002) defines illiquidity as the average ratio of the daily absolute return as a fraction of the (dollar) trading volume on that day and shows that market illiquidity is positively associated with future returns, providing evidence for an illiquidity premium. This result accords well with the prior cross-sectional findings. To overcome the bias induced by inflation over long horizons, Ben-Rephael et al. (2010) adjust the Amihud illiquidity measure for inflation and display that the illiquidity premium declines over the years.

Although liquidity is straightforward to define, it is not easily measured due to the limited availability of actual trading costs. In the U.S., transaction cost data is available since 1983, however, these costs are not available in many other countries. This adversity led researchers to look for liquidity proxies. The number of existing liquidity measures is vast and there is little or no correlation between these measures. Goyenko et al. (2009) provide a comprehensive study of different liquidity measures and document that the Amihud measure does well for capturing the price impact. They also note that the performance and accuracy of some liquidity measures may differ in stocks which are associated with thin trading. In this vein, using a log-transformed version of the Amihud measure, Karolyi et al. (2012) study the levels of commonality in liquidity in various countries and document that this co-movement in liquidity is abundant in countries with high average market volatility and weaker legal protection. In addition, by introducing a new liquidity measure which is a non-trading day adjusted version of the original Amihud measure, Kang and Zhang (2014) find it to be the best low-frequency illiquidity measure in emerging markets. In summary, there is little agreement about which measure is superior and whether these measures capture the real transaction costs.

Among several liquidity proxies, turnover may not be an accurate measure of liquidity. Lesmond (2005) examines a set of emerging markets and finds that turnover is not related to the common variation among the alternative liquidity metrics. This result casts doubt on the papers using turnover as a primary liquidity proxy. Barinov (2014) shows that there is no relation between turnover and alternative measures of liquidity risk and turnover is mostly negatively related to liquidity. The study also argues that turnover covaries with expected returns due to it being a proxy for the aggregate volatility risk factor. Considering the disagreement regarding the most suitable illiquidity measure, I examine the return-liquidity relation in Borsa Istanbul using the most comprehensive set of measures applicable.

Existing literature highlights the effect of liquidity on equity returns in U.S. markets. There exist some studies that investigate the return-liquidity relation in other individual markets and these studies obtain different conclusions by utilizing different liquidity proxies and covering different time periods.[3] There are also some multiple-country studies on this topic such as Bekaert et al. (2007) and Lee (2011).[4] My paper is different than these studies as I utilize more direct firm-level illiquidity metrics such as the Amihud (2002) and Pastor and Stambaugh (2003) measures compared to the monthly proportion of zero-return days used in Bekaert et al. (2007) and Lee (2011). Second, I offer a firm-level analysis rather than the country-level analysis in Bekaert et al. (2007) and I am able to use a wider set of control variables compared to the firm-level analysis in Lee (2011). Finally, focusing on a single country enables us to present a more detailed analysis of the relation between illiquidity and equity returns via utilizing univariate and bivariate portfolio analyses, incorporating extra asset pricing factors and market-wide variables and presenting transition probabilities to assess persistence.

2.3 Data and Methodology

2.3.1 Illiquidity Variables

Following Amihud (2002), I construct a monthly measure of illiquidity, $Illiq_{it}$ from daily equity returns and trading volumes as the average of the ratio of the daily absolute return to the Lira trading volume for each stock. Defining $|R_{idt}|$ as the return on stock i on day d of month t and VOL_{idt} as the respective daily volume, $Illiq_{it}$ can be more formally defined as:

$$Illiq_{it} = 1/D_{it} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{VOL_{idt}} \tag{2.1}$$

[3] See Lam and Tam (2011) for Hong Kong; Batten and Vo (2014) for Vietnam; Chan and Faff (2005) for Australia and Vaihekoski (2009) for Finland.

[4] Brockman et al. (2009) study liquidity in various countries and focus on commonality in liquidity across firms and exchanges. The dependent variables in all of their regressions are liquidity measures rather than equity returns.

where D_{it} is the number of days for which data are available for stock *i* in month *t*. This ratio gives the absolute price change per dollar of daily trading volume and is based on the concept of response of price to order flow.

Since average illiquidity changes drastically over the years, the mean-adjusted value of $Illiq_{it}$ is computed and utilized in the analysis after being multiplied by 10^6. To do so, I first calculate the average market illiquidity across stocks in each month as:

$$Avilliq_t = 1/N_t \sum_{i=1}^{N_t} Illiq_{it} \tag{2.2}$$

where N_t is the total number of stocks trading in each month *t*. Then, I form the mean-adjusted measure of illiquidity as:

$$IlliqMA_{it} = Illiq_{it} \,/\, Avilliq_t. \tag{2.3}$$

This measure reflects the relative liquidity of a stock with respect to other stocks in the market in a particular month.

Next, to control for inflationary effects over the sample period, following Ben-Rephael et al. (2010), I compute the inflation-adjusted version of $Illiq_{it}$ as:

$$IlliqRKW_{it} = 1/D_{it} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{VOL_{idt} \cdot inf_t} \tag{2.4}$$

where inf_t is the inflation adjustment factor.[5]

I further exploit the KLV_{it} measure which is proposed by Karolyi et al. (2012) by adding a constant term and using the log-transformed version of $Illiqmonth_{it}$ to reduce the effect of outliers.

$$KLV_{it} = 1/D_{it} \sum_{d=1}^{D_{it}} \left\{ ln\left(1 + \frac{|R_{idt}|}{VOL_{idt}}\right) \right\} \tag{2.5}$$

[5] The average annual inflation rate has been 70.4% and 9.3% for the periods between 1993-2002 and 2003-2013, respectively. High inflation is observed during the earlier period because Turkey was hit by several economic crises that triggered hyperinflation.

Furthermore, to take the non-trading days into account, I utilize the $Illiqzero_{it}$ measure which is proposed by Kang and Zhang (2014) as an adjusted version of the Amihud measure:

$$Illiqzero_{it} = \left[ln\left(\frac{1}{D_{it}}\sum_{d=1}^{D_{it}}\frac{|R_{idt}|}{VOL_{idt}}\right)\right] \times (1 + NT\%_{it}) \quad (2.6)$$

where $NT\%$ is the ratio of non-trading days in each month. Thin trading is more prevalent in emerging countries and the Amihud measure may not be a proper measure for stocks with many non-trading days. Therefore, $Illiqzero_{it}$ has the advantage of dealing with stale prices.

Finally, following Pastor and Stambaugh (2003), I construct the *Gamma* measure by running the following monthly regression:

$$R^{e}_{i,d+1,t} = \theta_{it} + \phi_{it}R_{idt} + \gamma_{it}\text{sign}(R^{e}_{idt}) \times VOL_{idt} + \varepsilon_{i,d+1,t} \qquad d=1,\ldots\ldots,D \qquad (2.7)$$

where R^{e}_{idt} is the return on stock *i* in excess of the market return, R_{idt} is the return on stock *i* on day *d* in month *t* and VOL_{idt} is the trading volume. The regression coefficient for signed volume, *Gamma* (γ_{it}), is multiplied by -1 to proxy for illiquidity. *Gamma* measures the reverse of the prior day's order flow shock. *Gamma* is expected to be negative and the absolute value of *Gamma* should increase with the implied price impact. Lower liquidity, therefore, corresponds to stronger volume-related return reversals.[6]

2.3.2 Data and Empirical Methodology

The equity returns and accounting data are primarily from Stockground.[7] The sample period is from January 1999 to December 2012. The stock price data is adjusted for stock splits, dividends and right offerings. Monthly stock returns are obtained by compounding

[6] Microstructure data such as bid-ask spreads are not available for Borsa Istanbul.
[7] StockGround is a financial analysis software with advanced fundamental and technical analysis capabilities designed by Rasyonet Inc., a software solution provider to brokerage houses, commercial banks and portfolio management firms.

daily returns. The market return is proxied by the return on the BIST-100 index. The risk-free rate is obtained from the Department of Treasury.

The test procedure follows the Fama-MacBeth (1973) methodology. A cross-sectional regression is estimated for each month in the sample period. For each of the 132 months in the sample, monthly stock returns are regressed on various illiquidity measures and firm characteristics:

$$R_{i,t+n} = \alpha_t + \beta_t ILLIQ_{it} + \delta_{1t} BETA_{it} + \delta_{2t} BM_{it} + \delta_{3t} SIZE_{it} + \delta_{4t} MOM_{it}\ \delta_{5t} STR_{it} + \varepsilon_{it} \quad (2.8)$$

where $R_{i,t+n}$ is the return on stock *i* for holding periods of *n* months after month *t*. I explore holding periods of one, three and six months. BM_{it} is the book-to-market ratio, $SIZE_{it}$ is natural logarithm of market capitalization, MOM_{it} is the momentum estimated as the lagged six-month cumulative return excluding the month prior to each monthly regression, STR_{it} is the lagged return for the past month which captures the short-term reversal effect and $ILLIQ_{it}$ represents various illiquidity measures.[8] These monthly regressions produce a time-series for each coefficient.[9] These monthly coefficient estimates are averaged and Newey-West (1987) standard errors, which take into account autocorrelation in the time-series of cross-sectional estimates, are used to test the statistical significance of these coefficient estimates.[10]

Following Fama and French (1992), I match the accounting data for all fiscal year ends in calendar year *j*-1 with the returns and market values between July of year *j* and June of year *j*+1 to ensure that the accounting variables are known before the returns they are used to explain. To be included in the return tests for July of year *j*, a firm must have stock price and market capitalization data for June of year *j* and book value of equity data for December of year *j*-1. It must also have monthly returns for at least 20 months during the 36 months preceding July of year *j* so that the beta estimates that are used in the Fama-MacBeth

[8] I also test a conditional asset pricing model for the existence of a link between illiquidity and expected returns. Specifically, I estimate a system of regressions where the excess returns of ten size portfolios are dependent variables and their conditional covariances with both the market return and illiquidity measures are explanatory variables. The conditional covariances are calculated by using a bivariate GARCH model. Results from these regressions which use time-fixed effects and clustered errors indicate that the conditional covariance between the returns of the asset classes and the illiquidity measures is statistically significantly priced.

[9] First 36 months are used to compute the beta coefficients, therefore, the first available month to perform the cross-sectional regression analysis is January 2002.

[10] A lag of 6 is used for the Newey-West correction. Results are robust for several other choices.

regressions can be estimated. To obtain the betas, I estimate the market model for each month from January 2002 to December 2012 by implementing a rolling window regression approach:

$$R_{it} = \alpha_{it} + BETA_{it} \times RM_t + \varepsilon_{it} \quad (2.9)$$

where RM_t is the value-weighted market return and $BETA_{it}$ is the slope coefficient estimated with a rolling windows of 36 months.[11] Outliers, defined as stocks whose estimated illiquidity proxies in year j-1 are in the highest or lowest 1% tails of the distribution, are excluded. Following Jegadeesh and Titman (1993), momentum is defined as the lagged six-month cumulative return excluding the month prior to each monthly regression in order to eliminate the autocorrelation effect of monthly returns.

I also conduct a univariate portfolio analysis by sorting stocks according to their illiquidity measures and observe the relative future performances of the high illiquidity portfolio and the low illiquidity portfolio in the future. More specifically, quintile portfolios are formed in each month between January 2002-December 2012 by sorting stocks according to their illiquidity metrics where quintile 5 contains highly illiquid stocks and quintile 1 contains stocks with the lowest illiquidity. Value-weighted average one-month ahead returns are computed in each quintile to investigate whether there exists a significant difference between the expected returns of the stocks in the high and low illiquidity quintiles. I also check whether the return differences between the extreme illiquidity quintiles can be explained by market, value, size and momentum factors. To do so, monthly return differences between extreme illiquidity quintiles are regressed on the four factors and I examine whether the alphas obtained from these regressions are statistically significant. Moreover, I employ dependent double sorts on firm size or return volatility and illiquidity to get a deeper understanding of the impact of these characteristics on the illiquidity premium.

[11] The models were re-estimated using betas of size portfolios as in Amihud (2002) in lieu of betas of individual stocks. Using these alternative betas does not have a material impact on the results regarding the relation between illiquidity metrics and future equity returns. Moreover, omitting beta from the cross-sectional regressions does not qualitatively alter the results.

2.4 Descriptive Statistics and Empirical Results

2.4.1 Descriptive Statistics

The overall sample consists of 37,382 monthly observations. Table 2.1 presents descriptive statistics along with correlations among six illiquidity measures. Statistics in Panel A of Table 2.1 are computed as the time-series averages of the cross-sectional values. I present the mean, median, standard deviation, skewness, and kurtosis for monthly returns, beta, book-to-market ratio, size, momentum and the six illiquidity variables defined earlier. Observe that stocks have a mean (median) monthly return of 2.25% (2.75%) with a standard deviation of 8.92%. The average beta is 0.86. The mean (median) book-to-market in my sample is 0.94 (0.85), while the mean (median) logarithm of size is 18.37 (18.51). There is also a significant dispersion in the momentum measure which has an average of 17.09% and a standard deviation of 27.30%. The Amihud illiquidity proxy (*Illiq*) has a mean of 0.2602 indicating that the absolute price change per million units of daily trading volume is approximately 26% which is close to Amihud's finding of 0.3370 for the U.S. markets. The inflation-adjusted (*IlliqRKW*) and the log-transformed (*KLV*) versions of the Amihud measures have mean values of 0.1285 and 0.2602, respectively. Both of these measures are positively skewed and leptokurtic. The mean-adjusted Amihud measure (*IlliqMA*) is slightly negatively skewed with a mean of 0.5089. *Illiqzero* displays a negative mean value of -3.3432. This measure is mechanically negative since I take the natural logarithm of *Illiq* before taking non-trading days into account. Pastor and Stambaugh (2003) reversal coefficient (*Gamma*) is highly leptokurtic with a mean (median) of 0.0030 (0.0013).

Panel B of Table 2.1 includes the time-series averages of the cross-sectional correlations among six illiquidity measures. As expected, the original, inflation-adjusted and log-transformed versions of the Amihud measure are highly correlated with each other. These measures are also positively correlated with *IlliqMA* and *Illiqzero*. *Gamma* seems to be weakly correlated with other measures. Figure 1 graphs *IlliqRKW* and *Gamma* over time. Illiquidity seems to boost after the 2001 Turkish banking crises and the more recent 2008 global credit crunch. Liquidity dries up at these financially harsh times. I conclude that the utilized liquidity measures are able to capture the general liquidity trends in Turkey.

Panel C of Table 2.1 presents average characteristics of portfolios formed by sorting stocks into quintiles based on *IlliqMA* each month. The characteristics I report are logarithmic market value of equity, return volatility measured as the standard deviation of daily returns in a given month, stock price, book-to-market ratio, market beta and momentum measured as the cumulative return over the past 6 months with a one-month lag. The results suggest that the equities in the highest illiquidity quintile have significantly lower market values of equity, stock prices, market betas and momentum returns compared to the equities in the lowest illiquidity quintile. Although less liquid stocks also seem to be more volatile and have a value tilt as evidenced by their higher book-to-market ratios, these differences are not statistically significant. These patterns continue to be observed when equities are sorted into quintiles based on other illiquidity metrics and I do not report them to conserve space.

2.4.2 Regression Analysis

Following the Fama-MacBeth (1973) methodology, cross-sectional regressions are run for each post-formation month, where the dependent variable is the one-, three, and six-month ahead returns on each stock and the independent variables are various illiquidity measures. I also use market beta, book-to-market ratio, the natural logarithm of market capitalization, momentum and one-month lagged return as control variables.

Table 2.2 presents the regression coefficients from six univariate regression specifications for various horizons. The reported coefficients are time-series averages and the reported t-statistics are based on the time-series variation of regression coefficients. Observe that all illiquidity variables are significantly and positively related to stock returns which suggests the existence of an illiquidity premium. For the one-month horizon, the t-statistics vary between 1.95 and 3.81. T-stats are larger for the three-month horizon with the sole exception of *Illiqzero* and they range from 2.22 to 3.43. *IlliqMA* and *Illiqzero* are both significant at the 1% level in all specifications. The coefficient of *Gamma* is significant at the 1% level for one- and three-month return horizons. To summarize, Amihud-based measures do well for explaining the relation between future stock returns and illiquidity which is consistent with existing U.S. studies. *Gamma*'s effectiveness in capturing the price impact in the data is in contrast with the U.S. results as Goyenko et al. (2009) find that *Gamma* is not a good proxy for measuring the price impact.

Table 2.3 augments the univariate specifications by including additional control variables and presents the results for the regression equation (2.8). In Panel A of Table 2.3, for the one-month return horizon, all illiquidity variables are positive and significant at least at the 10% level. Similar to the findings in Table 2.2, *IlliqMA*, *Illiqzero* and *Gamma* are significant at the 1% level with t-statistics of 3.04, 4.32 and 2.83, respectively. In Panel B of Table 2.3, for the three-month return horizon, all illiquidity variables are statistically significant at least at the 5% level. T-statistics of the coefficients of the illiquidity metrics are between 2.11 and 4.04. In Panel C of Table 2.3, I show that all illiquidity variables have positive and statistically significant coefficients except the Pastor and Stambaugh (2003) illiquidity proxy for which the t-statistic drops to 1.13. However, if I restrict my analysis after 2007, I regain its effect to covary with expected returns with a t-statistic of 1.98. *Illiqzero* and *Illiq* have the strongest statistical relation with future equity returns with t-statistics of 4.12 and 3.03, respectively. The seasonality effect is also investigated by running the regressions without January data or for the month of January only. In untabulated results, I find that seasonality does not affect the illiquidity premium.

When I focus on the control variables, I observe that market beta is not associated with cross-sectional equity returns. In line with the U.S. studies, the book-to-market ratio has a positive coefficient and firm size has a negative coefficient, however, both of them lack significance in the regressions. The statistical significance of the relation between expected returns and lagged monthly returns is weak for the one- and three-month return horizons whereas the average slope on lagged monthly returns becomes significantly negative for the six-month horizon. Finally, the results indicate that winner (loser) stocks turn out to be losers (winners) with statistically negative coefficients for the momentum variable for three- and six-month ahead returns. In other words, contrary to the existing U.S. studies, it seems more plausible to treat the momentum effect as a reversal effect in Turkish equity markets.

To check whether the illiquidity premium persists through time, I repeat the analysis by extending the sample. Having lived with high inflation during the 1990s, Turkey experienced severe financial crises such as the local banking crisis in 1994 and the Asian and Russian crises in 1998. I want to investigate whether the illiquidity premium also exists in an extended sample that includes these financially volatile times. Thus, Fama-MacBeth regressions are repeated using a longer sample period between 1992 and 2012. The results in Table 2.4 indicate that illiquidity proxies are highly significant in explaining the cross-sectional variation in equity returns. Similar to my previous findings, the illiquidity premium is stronger when the three-month ahead return is used as the dependent variable. For this return horizon, the t-statistics of the illiquidity metrics vary between 2.04 and 4.85. For the one-month and six-month windows, all illiquidity measures still have significantly positive coefficients at least at the 10% level with the exception of *Gamma* for the six-month horizon. Thus, I conclude that regardless of the sample period, there is a significantly positive relation between illiquidity and equity returns. The negative relation between future equity returns and both the lagged return and momentum variables is more pronounced when the extended sample is taken into account. Note that I focus on the refined sample in my analysis because the data quality is low, the markets are extremely small and there exists hyperinflation until 2002. Moreover, my study is motivated by the increase in foreign direct investment in Turkey which became more pronounced during the last decade.

2.4.3 Univariate Portfolio Analysis

Another method for examining the relation between illiquidity and expected stock returns is to use portfolio sorting and investigate the performance of zero-investment portfolios. In this section, I use portfolio analysis in which quintiles are formed by sorting stocks based on their illiquidity metrics and one-month ahead returns are calculated for each quintile to find out whether there exists a significant difference in future returns between stocks in the highest and lowest illiquidity quintiles.

Table 2.5 presents the time-series averages of illiquidity and value-weighted returns for each of these illiquidity-sorted portfolios.[12] For all illiquidity variables except *Gamma*, I see that the average return of the illiquidity portfolios increases from the lowest to the highest illiquidity quintile. The average monthly return difference between the extreme return quintiles is 1.6% which is significant at the 1% level. For *Gamma*, the average return

[12] The results are qualitatively similar for equal-weighted portfolio returns and are available upon request.

difference between the extreme portfolios is 0.6%. The average raw return differences between all of these portfolios are statistically significant. The findings are also economically significant. The results indicate that stocks in the highest illiquidity quintile generate about 19.2% (7.2% in the case of *Gamma*) higher annual returns in comparison with stocks in the lowest illiquidity quintile.

Moreover, I investigate whether the significant return difference between extreme illiquidity portfolios can be rationalized by Carhart's (1997) market, value, size and momentum factors. I should emphasize that these factors are not borrowed from any U.S. databases and I generate them myself by sorting all stocks to portfolios as explained below. To achieve my goal, monthly return differences between high and low illiquidity quintiles are regressed on the four factors and checked whether the intercepts in result of these regressions are statistically significant using the following model:

$$R_{t+n} = \alpha + \beta_{MKT} MKT_t + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{UMD} UMD_t + \varepsilon_{t+n} \qquad (2.10)$$

where R_{t+n} is the one-, three- and six-month ahead return of the zero-investment portfolios and MKT_t, HML_t, SMB_t and UMD_t are the market, value, size and momentum factors in month t, respectively. α is the return alpha and β_{MKT}, β_{HML}, β_{SMB} and β_{UMD} are the market, value, size and momentum betas, respectively. The market factor (*MKT*) is measured by the excess return on the BIST-100 index. I estimate the value (*HML*) and size (*SMB*) factors by forming quintile portfolios every month using sorts of stocks on their book-to-market ratios and market values of equity, respectively. Then, the average monthly return differences between the highest and lowest quintile portfolios are calculated. The momentum factor (*UMD*) is constructed as the return difference between the 30 percent of firms with the highest lagged six-month returns and the 30 percent of firms with the lowest lagged six-month returns.

Table 2.6 presents the intercepts from these regressions. In Panel A of Table 2.6, for one-month ahead returns, the 4-factor alpha for the return difference between quintile 5 and quintile 1 is 1.58% with a t-statistic of 3.46 when *Illiq* is used as the illiquidity variable. I also obtain statistically significant 4-factor alphas when I utilize *IlliqRKW, IlliqMA, KLV and Illiqzero.* For *Gamma*, the 4-factor alpha is 0.61% with a t-statistic of 2.09. Panels B and C which focus on three- and six-month ahead returns, show that the 4-factor alphas for the return differences between quintile 5 and quintile 1 are 4.24% and 7.47% with t-statistics of 3.61 and 3.67, respectively when *Illiq* is used as the illiquidity variable. The 4-factor alphas are also statistically significant when I utilize other illiquidity measures in both panels. These results suggest that after controlling for the market, value, size, and momentum factors, the return difference between the high and low illiquidity quintiles is still positive and significant. In other words, these four popular risk factors cannot fully account for the positive relationship between illiquidity and expected stock returns. Collectively, I conclude that there is a significantly positive relation between illiquidity and future equity returns.

I also investigate the relation between the illiquidity premium and some market-wide factors. The capital markets in Turkey have undergone major structural reforms in the past decade and these reforms may have had an impact on the relation between illiquidity and expected equity returns. Since these reforms were gradually implemented and their effects were only reflected in the markets over time, it is empirically difficult to identify specific dates for market reforms and carry out event studies around those dates. Instead, I proxy for the process of market reforms using the aggregate market capitalization (*Agg Mkt* Cap) in Borsa Istanbul and examine the link between this variable and the illiquidity premium. Additionally, I assess the magnitude of the illiquidity premium during periods of extreme market upswings and downswings by defining dummies for the 10% of months with the largest price drops in BIST-100 index (*Low Mkt Dum*) and 10% of months with the largest price increases in BIST-100 index (*High Mkt Dum*). In my empirical treatment, I regress the monthly return differences between high and low illiquidity quintiles based on *IlliqMA* on the four factors defined in equation (2.10) and various combinations of the three market variables defined above. The results are presented in Table 2.7. I find that the aggregate market capitalization has a negative albeit insignificant relation with the illiquidity premium in all specifications. Additionally, the illiquidity premium is higher (lower) during periods of extreme market downswings (upswings) as evidenced by the significantly positive (negative) coefficient of *Low Mkt Dum* (*High Mkt Dum*). In other words, when the market is doing well, the investors expect lower return premiums from illiquid stocks and vice versa. Only the market factor has a significantly positive coefficient among Carhart's (1997) four factors and the intercept terms retain its positive significance in all specifications extending my results from Table 2.6.

2.4.4 Double Sorts on Firm Size or Return Volatility and Illiquidity

Bali et al. (2005) and Bali and Cakici (2008) examine the correlations between various firm characteristics and the effects of these characteristics on expected equity returns. They point out that illiquidity is an attribute that is more common for smaller stocks and stocks with higher return volatility. In this section, to explore the stand-alone impact of illiquidity on future returns, I support my previous regression analysis with results from bivariate portfolio analysis. Specifically, each month I sort stocks into quintile portfolios based on their size as measured by market value of equity. Then, within each size quintile, I sort stocks into quintiles based on various illiquidity metrics. As a result, I obtain 25 conditionally double-sorted portfolios. If illiquidity has an effect on equity returns independent than that of firm size, then the one-month ahead return difference between the high and low illiquidity portfolios within each size quintile should be significantly positive. Similarly, I repeat this procedure by first sorting equities based on their return volatility and then by illiquidity. I measure return volatility as the standard deviation of daily returns in a given month for each stock. If illiquidity is independently priced with respect to volatility of returns, I expect to observe a significant return differential between extreme illiquidity quintiles within each volatility quintile.[13]

Panel A of Table 2.8 presents results for conditionally sorted portfolios on firm size and illiquidity. Focusing on the results for *Illiq*, I find that the one-month ahead return difference between the high and low illiquidity quintiles is 3.2% with a t-statistic of 2.61 within the smallest size quintile. For the second smallest size quintile, the return difference between the extreme liquidity quintiles is 3.30% and it has a t-statistic of 8.22. The significant illiquidity-based return difference persists in the other size quintiles except for the largest stocks. For this group, the return difference between the high and low illiquidity quintiles is

[13] I repeat this procedure by grouping stocks into monthly terciles rather quintiles using sequential sorts first on firm size or return volatility and then on illiquidity. The conclusions I draw from this extra analysis are consistent with my quintile-based bivariate portfolio analysis and are available upon request.

-0.20% with a t-statistic of -0.29. Very similar patterns are observed for the analysis based on *IlliqRKW*, *IlliqMA*, *KLV* and *Illiqzero* with the highest illiquidity premiums for the smallest stocks and insignificant return differentials for the largest stocks.

Panel B of Table 2.8 presents results for conditionally sorted portfolios on return volatility and illiquidity. When the illiquidity quintiles are formed based on *Illiq*, I observe that the return difference between the high and low illiquidity quintiles is positive with t-statistics ranging from 2.11 to 3.29. Importantly, the monthly illiquidity premium is 2.8% for the highest volatility quintile whereas it monotonically decreases to 0.9% for the lowest volatility quintile. Similar findings are observed for the other illiquidity metrics. I conclude that the effect of illiquidity on expected equity returns is distinct from that of volatility and it is stronger for the group of stocks with higher volatility.

2.4.5 Persistence of Illiquidity

In this section, I present results analysing the cross-sectional persistence of illiquidity. The persistence of any cross-sectional determinant of equity returns is important to investigate because if a certain equity attribute is not transitory, this would imply that investors could demand a premium or discount for holding a particular stock by forecasting its future attribute from its current attribute. For my purposes, if illiquidity is a persistent characteristic, I can interpret the existence of a return premium for an illiquid stock by arguing that the investors increase their required return for the stock in the expectation that the stock will continue to be illiquid in the future.

To examine the persistence of illiquidity, at each month *t*, all stocks in the sample are sorted into quintiles based on an ascending ordering of *IlliqMA*.[14] This procedure is repeated in month *t+k*. For each *IlliqMA* quintile portfolio in month *t*, the percentage of stocks that fall into each of the month *t+k IlliqMA* quintile portfolios is calculated. In Table 2.9, I present the time-series averages of these transition probabilities for quintile portfolios formed at lags of one, three and six months. Panel A shows that 85.78% of stocks that are in the lowest

[14] The discussion in this section is based on the results for *IlliqMA*; however, I obtain similar results for the other illiquidity metrics.

illiquidity quintile in a particular month continue to be in the same quintile one month later. Similarly, 76.49% of stocks that are in the highest illiquidity quintile in a particular month continue to be in the same quintile one month later. For each month *t* quintile, the highest percentage of stocks end up staying in the same illiquidity quintile during the next month, with the probabilities decreasing as the distance between the quintiles increases. The results presented for three- and six-month transition probabilities in Panels B and C paint a similar picture. The highest percentage in each row corresponds to the diagonal element indicating that a stock tends to stay in its own illiquidity quintile rather than moving into any other particular quintile. In other words, for a stock in any given quintile of *IlliqMA*, the most likely quintile for that stocks in month *t+k* is the same quintile as the stock's month *t* quintile. As far as six months after the portfolio formation period, 78.22% of stocks that are in the lowest illiquidity quintile and 63.52% of stocks that are in the highest illiquidity quintile in a particular month maintain their quintile placement. These overall results suggest that illiquidity is a highly persistent equity characteristic.

2.5 Conclusion

This chapter investigates the importance of liquidity in explaining the cross-sectional variation in expected stock returns in Borsa Istanbul over the sample period between January 2002 and December 2012. This is the first study that examines the illiquidity premium in the Turkish context by gathering a wide range of illiquidity proxies. First, I estimate parametric Fama-MacBeth cross-sectional regressions of one-, three- and six-month ahead equity returns on various illiquidity measures and control variables. Second, I utilize a portfolio analysis in which I sort stocks into quintiles based on their illiquidity metrics and examine each quintile's future expected return. The regression results reveal the existence of a positive illiquidity premium even after controlling for commonly used firm characteristics. In other words, stocks that are more illiquid yield significantly higher future returns. The results from the univariate portfolio analysis also suggest that, on average, stocks in the highest illiquidity quintile have significantly and economically higher returns compared to stocks in the lowest illiquidity quintile. Even after controlling for the market, value, size, and momentum factors, I find a positive and significant return difference between the high illiquidity and low illiquidity quintiles. I check whether my main results hold in an extended sample period and find that the positive relation between illiquidity and expected stock returns is not sensitive to the sample period. To understand the impact of firm size and return volatility, I employ dependent double sorts on these variables and illiquidity measures to find that the illiquidity premium is stronger for small stocks and stocks with higher volatility. Finally, additional regressions reveal that the illiquidity premium increases during periods of extremely low market returns and vice versa.

2.6 Tables

Table 2.1 Descriptive Statistics

This table presents summary statistics and correlation measures for the variables used in the study in addition to average equity characteristics for illiquidity-sorted quintile portfolios. Panel A reports descriptive statistics for the liquidity measures as well as the returns and control variables constructed using individual securities listed in Borsa Istanbul from January 2002 to December 2012. Statistics are computed as the time-series averages of the cross-sectional means. Return is the monthly return for each stock. Beta is the slope coefficient from the monthly time-series regression of monthly returns on market returns estimated with a rolling window of 36 months. BM is the ratio of book value of common shares divided by their market value. Size is the natural logarithm of the market capitalization. Momentum is the cumulative return over the past 6 months with a one-month lag. Illiq is the average of the daily ratio of the absolute return to the trading volume. IlliqRKW is the average of the daily ratio of the absolute return to the trading volume adjusted for inflation. IlliqMA is the mean-adjusted value of the average of daily ratio of the absolute return to the trading volume. KLV is the natural logarithm of one plus the average of the daily ratio of the absolute return to the trading volume. Illiqzero is the natural logarithm of the average of the daily ratio of the absolute return to the trading volume adjusted for no-trading days in a month. Gamma is the return reversal coefficient estimated using daily returns and volume data in a month, as in Pastor and Stambaugh (2003). The mean, median, standard deviation, skewness and kurtosis statistics are reported. Panel B reports the correlations among the illiquidity variables defined above. Panel C reports the average illiquidity, logarithmic size, return volatility, stock price, book-to-market ratio, market beta and momentum return statistics for quintile portfolios formed by sorting stocks based on IlliqMA each month.

Panel A: Descriptive Statistics

Variable	**Mean**	**Median**	**SD**	**Skewness**	**Kurtosis**
Return	0.0225	0.0275	0.0892	-0.2131	3.9127
Beta	0.8627	0.8662	0.0429	-0.1514	3.0409
BM	0.9379	0.8505	0.2938	0.8805	3.1644
Size	18.3729	18.5136	0.5692	-0.4908	2.0820
Momentum	0.1709	0.1444	0.2730	0.4243	3.3179
Illiq	0.2602	0.0744	0.4054	2.2813	7.7468
IlliqRKW	0.1285	0.0549	0.1625	2.0459	6.9217
IlliqMA	0.5089	0.5846	0.2705	-0.3506	1.8788
KLV	0.2602	0.0744	0.4054	2.2811	7.7454
Illiqzero	-3.3432	-3.6170	0.9670	0.6016	2.4465
Gamma	0.0030	0.0013	0.0051	2.1293	8.7186

Panel B: Cross-Sectional Correlations

	Illiq	IlliqRKW	IlliqMA	KLV	Illiqzero	Gamma
Illiq	1					
IlliqRKW	0.9996	1				
IlliqMA	0.7461	0.7443	1			
KLV	0.9999	0.9996	0.7461	1		
Illiqzero	0.6087	0.6078	0.5486	0.6087	1	
Gamma	0.1746	0.1737	0.1500	0.1746	0.1260	1

Table 2.1 (Continued)

Panel C: Characteristics for IlliqMA Quintiles

	Average Illiquidity	Average Size	Average Volatility	Average Price	Average BM	Average Beta	Average MOM
Low illiq.	0.022	20.3819	0.0277	7.2729	0.8300	0.9949	0.2034
2	0.098	18.6968	0.0281	5.2204	0.8977	0.9231	0.1939
3	0.229	18.0175	0.0283	4.0356	0.9115	0.8475	0.1543
4	0.482	17.6568	0.0280	3.4684	0.9743	0.7989	0.1396
High illiq.	2.094	17.0912	0.0284	3.5770	0.8711	0.7321	0.1168
High-Low		-3.2907	0.0006	-3.6959	0.0412	-0.2628	-0.0866
		(-96.44)	(1.61)	(-6.52)	(1.12)	(-38.89)	(-8.31)

Table 2.2 Univariate Fama-MacBeth Cross-Sectional Regressions

This table presents results from the cross-sectional regressions of future equity returns on illiquidity measures over the period from January 2002 to December 2012. In Panels A, B and C, the dependent variable is the one-month, three-month and six-month ahead returns, respectively. The illiquidity measures are defined in Table 2.1. Reported coefficients are time-series averages and the associated t-statistics are reported using the Newey-West (1987) procedure. Average R-squared is presented at the last row of each panel.

Panel A: 1-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.025	(2.17)										
IlliqRKW			0.037	(1.95)								
IlliqMA					0.005	(2.65)						
KLV							0.025	(2.18)				
Illiqzero									0.003	(3.81)		
Gamma											0.212	(2.72)
Constant	0.021	(2.51)	0.021	(2.51)	0.021	(2.51)	0.021	(2.51)	0.035	(3.97)	0.023	(2.72)
R-squared	0.0161		0.0157		0.0117		0.0161		0.0178		0.0063	

Panel B: 3-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.084	(2.30)										
IlliqRKW			0.126	(2.22)								
IlliqMA					0.015	(3.31)						
KLV							0.084	(2.31)				
Illiqzero									0.012	(3.43)		
Gamma											0.512	(2.84)
Constant	0.068	(2.71)	0.068	(2.71)	0.069	(2.75)	0.068	(2.71)	0.113	(3.99)	0.074	(2.96)
R-squared	0.0197		0.0197		0.0127		0.0196		0.0159		0.0062	

Panel C: 6-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.115	(2.05)										
IlliqRKW			0.174	(2.02)								
IlliqMA					0.027	(2.60)						
KLV							0.113	(2.05)				
Illiqzero									0.024	(3.32)		
Gamma											0.464	(1.64)
Constant	0.150	(3.02)	0.150	(3.02)	0.152	(3.01)	0.150	(3.02)	0.235	(4.19)	0.160	(3.19)
R-squared	0.0163		0.0163		0.0140		0.0162		0.0152		0.0062	

Table 2.3 Multivariate Fama-MacBeth Cross-Sectional Regressions

This table presents results from the cross-sectional regressions of future equity returns on illiquidity measures and control variables over the period from January 2002 to December 2012. In Panels A, B and C, the dependent variable is the one-month, three-month and six-month ahead returns, respectively. The illiquidity measures and control variables are defined in Table 2.1. Reported coefficients are time-series averages and the associated t-statistics are reported using the Newey-West (1987) procedure. Average R-squared is presented at the last row of each panel.

Panel A: 1-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.022	(1.88)										
IlliqRKW			0.035	(1.67)								
IlliqMA					0.005	(3.04)						
KLV							0.022	(1.88)				
Illiqzero									0.005	(4.32)		
Gamma											0.199	(2.83)
Beta	0.003	(0.67)	0.003	(0.64)	0.004	(0.73)	0.003	(0.67)	0.006	(1.18)	0.003	(0.56)
BM	0.001	(0.76)	0.001	(0.69)	0.001	(1.02)	0.001	(0.76)	0.000	(0.06)	0.001	(0.69)
Size	-0.001	(-0.82)	-0.001	(-0.84)	-0.001	(-0.84)	-0.001	(-0.83)	0.001	(0.58)	-0.001	(-1.19)
STR	0.002	(0.12)	0.002	(0.12)	-0.002	(-0.13)	0.002	(0.13)	0.002	(0.12)	0.003	(0.19)
Momentum	-0.007	(-1.43)	-0.007	(-1.44)	-0.010	(-2.27)	-0.007	(-1.43)	-0.006	(-1.20)	-0.006	(-1.17)
Constant	0.036	(1.30)	0.037	(1.32)	0.035	(1.38)	0.036	(1.30)	0.017	(0.60)	0.044	(1.80)
R-squared	0.0879		0.0875		0.0803		0.0879		0.0844		0.0824	

Panel B: 3-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.083	(2.20)										
IlliqRKW			0.133	(2.11)								
IlliqMA					0.014	(3.28)						
KLV							0.083	(2.20)				
Illiqzero									0.015	(4.04)		
Gamma											0.482	(2.88)
Beta	0.009	(0.60)	0.009	(0.59)	0.010	(0.68)	0.009	(0.60)	0.018	(1.14)	0.006	(0.42)
BM	0.004	(1.47)	0.004	(1.46)	0.005	(1.75)	0.004	(1.47)	0.003	(0.94)	0.005	(1.53)
Size	-0.005	(-0.87)	-0.005	(-0.88)	-0.004	(-0.98)	-0.005	(-0.87)	0.002	(0.34)	-0.006	(-1.27)
STR	-0.031	(-1.30)	-0.031	(-1.30)	-0.032	(-1.39)	-0.031	(-1.29)	-0.033	(-1.39)	-0.032	(-1.28)
Momentum	-0.025	(-2.16)	-0.025	(-2.16)	-0.031	(-3.00)	-0.025	(-2.17)	-0.023	(-1.81)	-0.024	(-1.96)
Constant	0.133	(1.34)	0.133	(1.35)	0.131	(1.52)	0.132	(1.34)	0.072	(0.78)	0.170	(1.87)
R-squared	0.0890		0.0889		0.0786		0.0889		0.0800		0.0775	

Panel C: 6-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.110	(1.90)										
IlliqRKW			0.179	(1.91)								
IlliqMA					0.026	(3.03)						
KLV							0.108	(1.89)				
Illiqzero									0.026	(4.12)		
Gamma											0.327	(1.13)
Beta	0.013	(0.43)	0.013	(0.43)	0.013	(0.46)	0.013	(0.43)	0.030	(1.06)	0.006	(0.20)
BM	0.010	(1.71)	0.010	(1.70)	0.014	(2.45)	0.010	(1.70)	0.008	(1.28)	0.009	(1.31)
Size	-0.012	(-1.07)	-0.012	(-1.07)	-0.012	(-1.12)	-0.012	(-1.07)	-0.002	(-0.12)	-0.014	(-1.35)
STR	-0.086	(-2.36)	-0.087	(-2.36)	-0.084	(-2.26)	-0.086	(-2.35)	-0.086	(-2.36)	-0.095	(-2.54)
Momentum	-0.051	(-2.92)	-0.051	(-2.92)	-0.056	(-3.36)	-0.051	(-2.92)	-0.048	(-2.54)	-0.052	(-2.77)
Constant	0.341	(1.58)	0.341	(1.58)	0.339	(1.66)	0.342	(1.58)	0.232	(1.05)	0.396	(1.96)
R-squared	0.0817		0.0817		0.0777		0.0816		0.0764		0.0715	

Table 2.4 Extended-Sample Multivariate Fama-MacBeth Cross-Sectional Regressions

This table presents results from the cross-sectional regressions of future equity returns on illiquidity measures and control variables over the period from January 1992 to December 2012. In Panels A, B and C, the dependent variable is the one-month, three-month and six-month ahead returns, respectively. The illiquidity measures and control variables are defined in Table 2.1. Reported coefficients are time-series averages and the associated t-statistics are reported using the Newey-West (1987) procedure. Average R-squared is presented at the last row of each panel.

Panel A: 1-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.014	(1.84)										
IlliqRKW			0.023	(1.79)								
IlliqMA					0.004	(2.52)						
KLV							0.014	(1.84)				
Illiqzero									0.005	(5.19)		
Gamma											0.132	(2.80)
Beta	0.002	(0.37)	0.001	(0.16)	0.002	(0.30)	0.002	(0.37)	0.008	(1.36)	0.003	(0.58)
BM	0.000	(0.21)	0.000	(-0.04)	0.000	(0.12)	0.000	(0.21)	0.000	(0.17)	0.001	(0.57)
Size	-0.002	(-1.46)	-0.002	(-1.57)	-0.002	(-1.69)	-0.002	(-1.46)	0.001	(0.42)	-0.002	(-1.81)
STR	-0.006	(-0.58)	-0.007	(-0.67)	-0.009	(-0.88)	-0.006	(-0.57)	-0.005	(-0.45)	-0.004	(-0.40)
Momentum	-0.011	(-3.14)	-0.011	(-3.06)	-0.012	(-3.88)	-0.011	(-3.14)	-0.010	(-2.85)	-0.009	(-2.60)
Constant	0.069	(2.60)	0.074	(2.71)	0.074	(2.81)	0.069	(2.60)	0.034	(1.24)	0.074	(3.09)
R-squared	0.1122		0.1108		0.1055		0.1122		0.1097		0.1045	

Panel B: 3-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.051	(2.11)										
IlliqRKW			0.083	(2.08)								
IlliqMA					0.010	(2.04)						
KLV							0.050	(2.11)				
Illiqzero									0.014	(4.85)		
Gamma											0.297	(2.65)
Beta	0.002	(0.09)	0.001	(0.03)	0.002	(0.10)	0.002	(0.09)	0.020	(0.91)	0.002	(0.12)
BM	0.002	(0.34)	0.001	(0.26)	0.002	(0.33)	0.002	(0.34)	0.002	(0.28)	0.002	(0.27)
Size	-0.008	(-1.82)	-0.008	(-1.87)	-0.008	(-2.08)	-0.008	(-1.82)	-0.001	(-0.16)	-0.008	(-2.14)
STR	-0.063	(-3.28)	-0.064	(-3.30)	-0.065	(-3.41)	-0.063	(-3.28)	-0.065	(-3.42)	-0.066	(-3.32)
Momentum	-0.029	(-3.28)	-0.029	(-3.28)	-0.032	(-3.75)	-0.029	(-3.28)	-0.027	(-2.81)	-0.028	(-3.03)
Constant	0.251	(2.93)	0.257	(2.98)	0.262	(3.18)	0.250	(2.93)	0.154	(1.89)	0.271	(3.38)
R-squared	0.1040		0.1030		0.0973		0.1040		0.0984		0.0939	

Panel C: 6-month Ahead Returns

	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Illiq	0.067	(1.86)										
IlliqRKW			0.121	(2.06)								
IlliqMA					0.019	(2.58)						
KLV							0.066	(1.85)				
Illiqzero									0.026	(5.09)		
Gamma											0.283	(1.59)
Beta	0.018	(0.39)	0.018	(0.39)	0.019	(0.42)	0.017	(0.39)	0.050	(1.03)	0.013	(0.29)
BM	-0.004	(-0.23)	-0.003	(-0.21)	-0.001	(-0.07)	-0.004	(-0.23)	-0.003	(-0.22)	-0.004	(-0.27)
Size	-0.016	(-1.82)	-0.016	(-1.82)	-0.017	(-1.97)	-0.016	(-1.82)	-0.003	(-0.37)	-0.017	(-2.04)
STR	-0.115	(-3.54)	-0.115	(-3.54)	-0.113	(-3.33)	-0.115	(-3.53)	-0.118	(-3.49)	-0.123	(-3.62)
Momentum	-0.045	(-2.94)	-0.044	(-2.90)	-0.048	(-3.29)	-0.045	(-2.94)	-0.041	(-2.62)	-0.045	(-2.80)
Constant	0.528	(3.07)	0.527	(3.08)	0.542	(3.19)	0.529	(3.07)	0.343	(2.08)	0.562	(3.37)
R-squared	0.0967		0.0971		0.0937		0.0966		0.0964		0.0897	

Table 2.5 Univariate Portfolio Analysis with Value-Weighted Returns

This table presents return comparisons between equity quintiles formed based on illiquidity measures. The quintile portfolios are formed every month from January 2002 to December 2012. Quintile 1 is the portfolio of stocks with the lowest illiquidity and Quintile 5 is the portfolio of stocks with the highest illiquidity. The value-weighted monthly portfolio returns are calculated for each portfolio. The table reports the average illiquidity in each quintile and the one-month ahead returns. The last row shows the differences of monthly returns between quintiles 5 and 1. The illiquidity measures are defined in Table 2.1. Newey-West (1987) adjusted t-statistics are presented in parentheses.

	Illiq		**IlliqRKW**		**IlliqMA**	
	Average illiquidity in each quintile	Next month average returns	Average illiquidity in each quintile	Next month average returns	Average illiquidity in each quintile	Next month average returns
Low illiq.	0.005	0.018	0.003	0.018	0.022	0.017
2	0.027	0.018	0.015	0.018	0.098	0.018
3	0.065	0.019	0.036	0.019	0.229	0.019
4	0.154	0.023	0.084	0.023	0.482	0.023
High illiq.	1.415	0.034	0.694	0.034	2.094	0.033
High-Low		0.016		0.016		0.016
		(4.05)		(4.07)		(4.21)

	KLV		**Illiqzero**		**Gamma**	
	Average illiquidity in each quintile	Next month average returns	Average illiquidity in each quintile	Next month average returns	Average illiquidity in each quintile	Next month average returns
Low illiq.	0.005	0.018	-5.861	0.018	-0.022	0.024
2	0.027	0.018	-4.137	0.018	-0.002	0.018
3	0.065	0.019	-3.261	0.019	0.000	0.018
4	0.154	0.023	-2.475	0.024	0.004	0.019
High illiq.	1.401	0.034	-1.132	0.034	0.034	0.030
High-Low		0.016		0.016		0.006
		(4.07)		(3.99)		(2.28)

Table 2.6 Multivariate Regressions of Zero-Investment Portfolio Returns

This table presents the intercepts from multivariate regressions of one-month, three-month and six-month ahead average return differences between two extreme illiquidity quintiles on the market, value, size, and momentum factors. The quintile portfolios are formed every month from January 2002 to December 2012. The illiquidity measures are defined in Table 2.1. Newey-West (1987) adjusted t-statistics are presented in parentheses.

	Illiq	IlliqRKW	IlliqMA	KLV	Illiqzero	Gamma
Panel A: 1-Month Ahead Returns						
Alphas	0.0158	0.0159	0.0160	0.0159	0.0156	0.0061
	(3.46)	(3.47)	(3.53)	(3.47)	(3.39)	(2.09)
Panel B: 3-Month Ahead Returns						
Alphas	0.0424	0.0426	0.0393	0.0425	0.0418	0.0146
	(3.61)	(3.62)	(3.69)	(3.62)	(3.57)	(2.15)
Panel C: 6-Month Ahead Returns						
Alphas	0.0747	0.0764	0.0728	0.0763	0.0753	0.0131
	(3.67)	(3.68)	(3.55)	(3.59)	(3.56)	(1.83)

Table 2.7 Effects of Market Capitalization and Extreme Market Returns

This table presents the intercepts from multivariate regressions of one-month ahead average return differences between two extreme IlliqMA quintiles on the market, value, size, and momentum factors and various market characteristics. Agg Mkt Cap is the aggregate market capitalization for equities listed in Borsa Istanbul. Low Mkt Dum is equal to one for the ten percent of months during which the BIST-100 index displays the highest value decrease and zero otherwise. High Mkt Dum is equal to one for the ten percent of months during which the BIST-100 index displays the highest value increase and zero otherwise. The quintile portfolios are formed every month from January 2002 to December 2012. Newey-West (1987) adjusted t-statistics are presented in parentheses.

Constant	MKT	SMB	HML	UMD	Agg Mkt Cap	Low Mkt Dum	High Mkt Dum
0.0237					-0.0277		
(3.06)					(-1.07)		
0.0236	0.1063	0.1240	0.0546	-0.0185	-0.0316		
(2.82)	(1.99)	(1.24)	(0.34)	(-0.15)	(-1.17)		
0.0172	0.1170	0.1175	0.0141	0.0175		0.0368	
(2.09)	(2.28)	(1.27)	(0.09)	(0.15)		(3.69)	
0.0296	0.0872	0.1239	0.0627	-0.0543			-0.0451
(3.46)	(1.62)	(1.32)	(0.43)	(-0.47)			(-2.72)
0.0201	0.1202	0.1168	0.0138	0.0182	-0.0296	0.0354	
(2.37)	(2.36)	(1.26)	(0.09)	(0.15)	(-1.12)	(3.53)	
0.0321	0.0922	0.1228	0.0596	-0.0517	-0.0481		-0.0447
(3.74)	(1.73)	(1.32)	(0.41)	(-0.45)	(-1.77)		(-2.69)

Table 2.8 Additional Sorts by Firm Size and Return Volatility

This table presents return comparisons between equity quintiles formed based on sequential double sorts of firm size (Panel A) or return volatility (Panel B) and illiquidity. Firm size is measured by the market value of equity and return volatility is measured by the standard deviation of daily returns in a given month. The quintile portfolios are formed every month from January 2002 to December 2012. The value-weighted monthly portfolio returns are calculated for each portfolio. The last row shows the differences of monthly returns between illiquidity quintiles 5 and 1 for each firm size or return volatility quintile. The illiquidity measures are defined in Table 2.1. Newey-West (1987) adjusted t-statistics are presented in parentheses.

Panel A. Double Sorts on Firm Size and Illiquidity

Illiq

	Small	2	3	4	Large
Low illiq.	0.014	0.001	0.013	0.011	0.021
	(1.15)	(0.11)	(1.28)	(1.00)	(2.33)
2	0.021	0.027	0.025	0.038	0.023
	(2.16)	(3.11)	(2.67)	(3.41)	(2.46)
3	0.035	0.021	0.025	0.021	0.019
	(4.03)	(2.43)	(2.49)	(2.54)	(2.15)
4	0.035	0.024	0.025	0.021	0.017
	(3.08)	(2.65)	(2.93)	(2.40)	(1.91)
High illiq.	0.045	0.034	0.030	0.028	0.019
	(3.41)	(3.58)	(3.06)	(3.23)	(2.69)
High-Low	0.032	0.033	0.017	0.016	-0.002
	(2.61)	(8.22)	(2.29)	(2.34)	(-0.29)

IlliqRKW

	Small	2	3	4	Large
Low illiq.	0.014	0.001	0.013	0.012	0.020
	(1.16)	(0.12)	(1.29)	(1.07)	(2.29)
2	0.021	0.027	0.026	0.038	0.023
	(2.17)	(3.10)	(2.70)	(3.43)	(2.47)
3	0.035	0.021	0.024	0.021	0.019
	(4.02)	(2.42)	(2.44)	(2.52)	(2.14)
4	0.035	0.024	0.024	0.021	0.017
	(3.10)	(2.67)	(2.92)	(2.41)	(1.92)
High illiq.	0.045	0.033	0.030	0.028	0.019
	(3.39)	(3.56)	(3.08)	(3.21)	(2.72)
High-Low	0.032	0.032	0.017	0.016	-0.001
	(2.60)	(7.89)	(2.34)	(2.33)	(-0.17)

IlliqMA

	Small	2	3	4	Large
Low illiq.	0.016	0.002	0.020	0.013	0.018
	(1.27)	(0.22)	(1.66)	(1.14)	(1.98)
2	0.020	0.025	0.021	0.033	0.022
	(2.11)	(2.90)	(2.38)	(3.36)	(2.35)
3	0.036	0.021	0.024	0.020	0.023
	(3.82)	(2.48)	(2.40)	(2.45)	(2.73)
4	0.032	0.023	0.026	0.020	0.018
	(2.77)	(2.56)	(3.03)	(2.43)	(1.96)
High illiq.	0.049	0.033	0.028	0.027	0.019
	(3.69)	(3.44)	(3.17)	(3.14)	(2.67)
High-Low	0.033	0.031	0.009	0.014	0.001
	(2.62)	(7.95)	(1.11)	(1.93)	(0.11)

KLV

	Small	2	3	4	Large
Low illiq.	0.013	0.001	0.013	0.012	0.021
	(1.14)	(0.11)	(1.29)	(1.07)	(2.30)
2	0.021	0.027	0.026	0.038	0.023
	(2.16)	(3.08)	(2.69)	(3.41)	(2.46)
3	0.035	0.022	0.024	0.021	0.019
	(4.03)	(2.50)	(2.46)	(2.54)	(2.17)
4	0.035	0.024	0.025	0.021	0.017
	(3.08)	(2.64)	(2.95)	(2.39)	(1.91)
High illiq.	0.046	0.034	0.030	0.028	0.019
	(3.43)	(3.57)	(3.06)	(3.23)	(2.68)
High-Low	0.032	0.033	0.017	0.016	-0.001
	(2.65)	(8.21)	(2.29)	(2.34)	(-0.27)

Illiqzero

	Small	2	3	4	Large
Low illiq.	0.013	0.001	0.013	0.012	0.020
	(1.13)	(0.16)	(1.29)	(1.08)	(2.25)
2	0.021	0.027	0.025	0.038	0.023
	(2.14)	(3.06)	(2.63)	(3.41)	(2.46)
3	0.036	0.021	0.025	0.021	0.019
	(4.10)	(2.43)	(2.53)	(2.51)	(2.21)
4	0.035	0.025	0.023	0.021	0.017
	(3.08)	(2.72)	(2.70)	(2.44)	(1.94)
High illiq.	0.045	0.034	0.031	0.027	0.020
	(3.41)	(3.59)	(3.15)	(3.13)	(2.73)
High-Low	0.032	0.032	0.018	0.015	-0.001
	(2.66)	(7.78)	(2.40)	(2.19)	(-0.13)

Gamma

	Small	2	3	4	Large
Low illiq.	0.025	0.025	0.019	0.026	0.015
	(2.49)	(2.86)	(2.44)	(3.01)	(1.93)
2	0.024	0.012	0.023	0.023	0.023
	(2.48)	(1.32)	(2.08)	(2.37)	(2.69)
3	0.029	0.018	0.019	0.016	0.020
	(2.70)	(2.07)	(1.88)	(1.70)	(2.24)
4	0.023	0.025	0.023	0.018	0.021
	(2.06)	(2.50)	(2.39)	(2.04)	(2.30)
High illiq.	0.041	0.026	0.038	0.028	0.021
	(3.60v	(3.02)	(3.75)	(3.15)	(2.50)
High-Low	0.016	0.001	0.019	0.002	0.007
	(1.86)	(0.28)	(3.13)	(0.52)	(1.47)

Table 2.8 (Continued)

Panel B. Double Sorts on Return Volatility and Illiquidity

Illiq

	Low Vol	2	3	4	High Vol
Low illiq.	0.017	0.022	0.020	0.019	0.009
	(1.98)	(2.55)	(2.37)	(1.87)	(0.94)
2	0.018	0.021	0.022	0.028	0.010
	(2.03)	(2.60)	(2.40)	(2.13)	(0.95)
3	0.021	0.028	0.018	0.025	0.012
	(2.56)	(2.89)	(1.98)	(2.52)	(1.31)
4	0.029	0.029	0.028	0.027	0.012
	(3.67)	(3.16)	(3.51)	(2.40)	(1.33)
High illiq.	0.026	0.037	0.034	0.043	0.038
	(3.15)	(4.37)	(3.93)	(3.92)	(2.97)
High-Low	0.009	0.015	0.014	0.025	0.028
	(2.11)	(2.66)	(3.29)	(3.18)	(2.68)

IlliqRKW

	Low Vol	2	3	4	High Vol
Low illiq.	0.017	0.022	0.020	0.018	0.009
	(1.97)	(2.58)	(2.32)	(1.84)	(0.95)
2	0.018	0.021	0.022	0.028	0.010
	(2.04)	(2.59)	(2.42)	(2.15)	(0.94)
3	0.021	0.029	0.019	0.024	0.012
	(2.55)	(2.89)	(1.98)	(2.49)	(1.33)
4	0.029	0.029	0.028	0.027	0.012
	(3.69)	(3.14)	(3.52)	(2.44)	(1.34)
High illiq.	0.026	0.037	0.034	0.043	0.037
	(3.16)	(4.34)	(3.94)	(3.92)	(2.98)
High-Low	0.009	0.014	0.015	0.025	0.028
	(2.14)	(2.63)	(3.28)	(3.19)	(2.66)

IlliqMA

	Low Vol	2	3	4	High Vol
Low illiq.	0.016	0.022	0.022	0.020	0.007
	(1.92)	(2.55)	(2.45)	(1.89)	(0.73)
2	0.018	0.021	0.018	0.026	0.013
	(2.04)	(2.47)	(2.08)	(2.11)	(1.25)
3	0.021	0.029	0.020	0.024	0.012
	(2.53)	(3.01)	(2.13)	(2.56)	(1.24)
4	0.028	0.030	0.027	0.029	0.010
	(3.58)	(3.25)	(3.41)	(2.66)	(1.14)
High illiq.	0.028	0.035	0.034	0.041	0.038
	(3.31)	(4.45)	(3.87)	(3.64)	(3.12)
High-Low	0.012	0.013	0.012	0.021	0.031
	(2.61)	(2.49)	(2.91)	(2.90)	(3.22)

KLV

	Low Vol	2	3	4	High Vol
Low illiq.	0.017	0.022	0.020	0.019	0.009
	(1.98)	(2.55)	(2.36)	(1.87)	(0.95)
2	0.018	0.021	0.022	0.028	0.009
	(2.03)	(2.60)	(2.40)	(2.14)	(0.93)
3	0.021	0.028	0.018	0.024	0.012
	(2.56)	(2.89)	(1.98)	(2.50)	(1.32)
4	0.029	0.029	0.028	0.027	0.011
	(3.67)	(3.16)	(3.51)	(2.40)	(1.31)
High illiq.	0.026	0.037	0.034	0.043	0.038
	(3.15)	(4.37)	(3.93)	(3.92)	(2.98)
High-Low	0.009	0.015	0.014	0.025	0.028
	(2.11)	(2.66)	(3.30)	(3.18)	(2.69)

Illiqzero

	Low Vol	2	3	4	High Vol
Low illiq.	0.017	0.022	0.020	0.019	0.010
	(1.98)	(2.54)	(2.36)	(1.87)	(0.97)
2	0.018	0.022	0.021	0.027	0.009
	(2.08)	(2.64)	(2.34)	(2.11)	(0.87)
3	0.021	0.028	0.019	0.026	0.013
	(2.52)	(2.86)	(2.00)	(2.61)	(1.33)
4	0.028	0.029	0.027	0.027	0.012
	(3.67)	(3.16)	(3.47)	(2.39)	(1.35)
High illiq.	0.026	0.037	0.035	0.043	0.038
	(3.15)	(4.37)	(3.95)	(3.87)	(2.96)
High-Low	0.009	0.015	0.015	0.024	0.028
	(2.10)	(2.67)	(3.33)	(3.08)	(2.62)

Gamma

	Low Vol	2	3	4	High Vol
Low illiq.	0.029	0.025	0.025	0.021	0.022
	(3.81)	(3.10)	(3.11)	(1.96)	(1.90)
2	0.015	0.020	0.019	0.028	0.007
	(1.84)	(2.66)	(2.05)	(2.09)	(0.81)
3	0.020	0.025	0.022	0.024	0.012
	(2.29)	(2.83)	(2.48)	(2.40)	(1.12)
4	0.017	0.024	0.026	0.023	0.014
	(2.04)	(2.49)	(2.79)	(2.72)	(1.57)
High illiq.	0.028	0.042	0.030	0.035	0.025
	(3.48)	(3.97)	(3.76)	(3.32)	(2.40)
High-Low	-0.001	0.017	0.005	0.013	0.003
	(-0.30)	(2.95)	(1.14)	(2.80)	(0.38)

Table 2.9 Transition Probabilities

The tables below present the transition matrices for IlliqMA at lags of one, three and six months. At each month t, all stocks in the sample are sorted into quintiles based on an ascending ordering of IlliqMA. The procedure is repeated in month t+k. For each IlliqMA quintile portfolio in month t, the percentage of stocks that fall into each of the month t+k IlliqMA quintile portfolios is calculated. The tables present the time-series averages of these transition probabilities. Each row corresponds to a different month t IlliqMA portfolio and each column corresponds to a month t+k IlliqMA portfolio. IlliqMA is defined in Table 2.1. Panel A presents results for portfolios formed one month apart (k=1). Panel B presents results for portfolios formed three months apart (k=3). Panel C presents results for portfolios formed six months apart (k=6).

Panel A: Portfolios Formed One Month Apart

	Future Low illiq.	**2**	**3**	**4**	**Future High illiq.**
Low illiq.	85.78%	13.61%	0.51%	0.07%	0.04%
2	13.25%	61.28%	22.84%	2.44%	0.19%
3	0.93%	21.40%	51.54%	24.00%	2.13%
4	0.12%	3.06%	22.12%	53.67%	21.03%
High illiq.	0.02%	0.55%	2.98%	19.96%	76.49%

Panel B: Portfolios Formed Three Months Apart

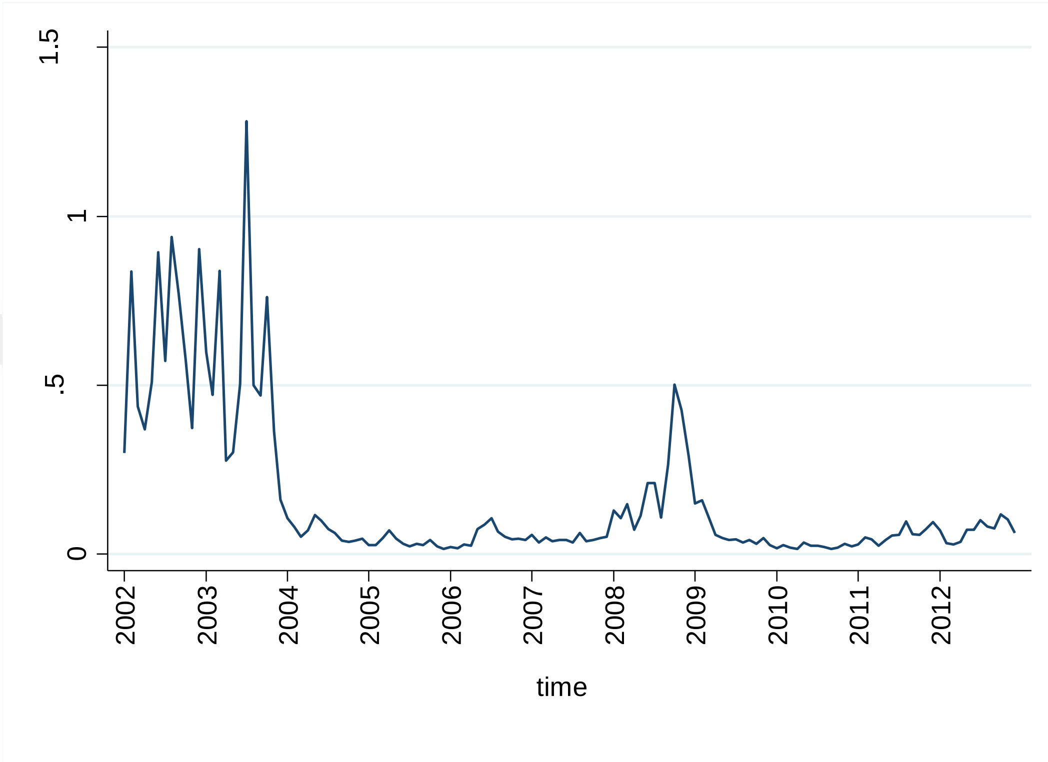
	Future Low illiq.	**2**	**3**	**4**	**Future High illiq.**
Low illiq.	81.44%	16.65%	1.66%	0.18%	0.07%
2	15.39%	51.26%	26.78%	5.91%	0.67%
3	2.71%	23.18%	41.29%	27.21%	5.61%
4	0.50%	7.10%	23.85%	43.74%	24.81%
High illiq.	0.19%	1.59%	6.34%	23.11%	68.78%

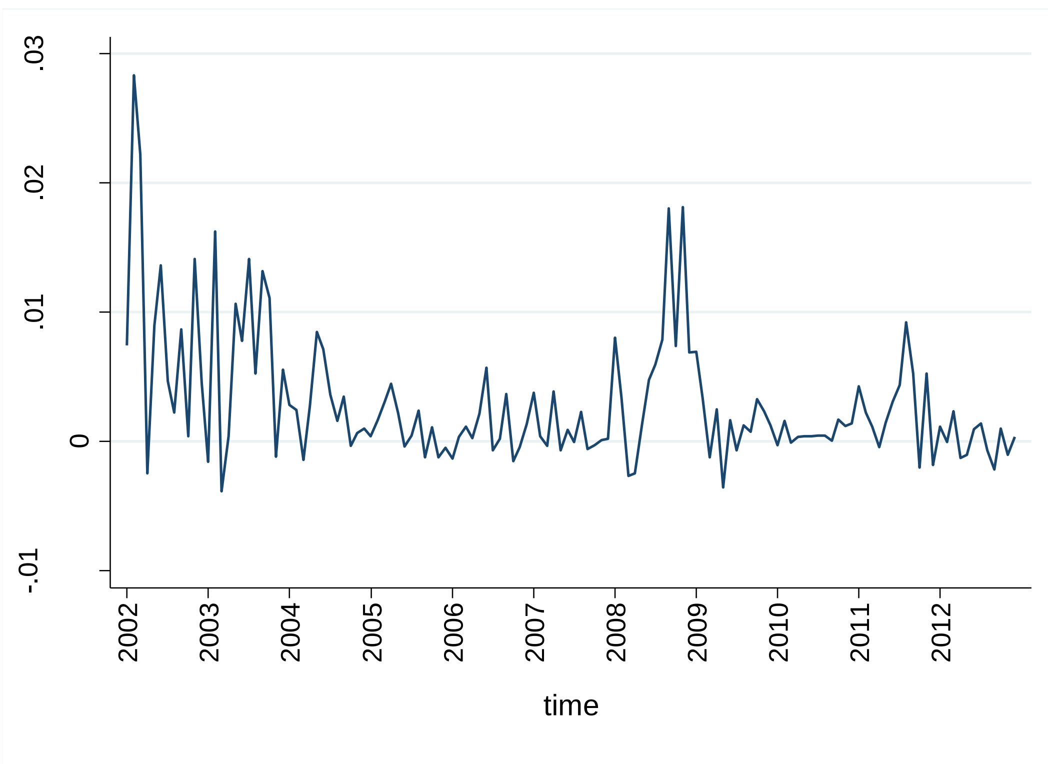
Panel C: Portfolios Formed Six Months Apart

	Future Low illiq.	**2**	**3**	**4**	**Future High illiq.**
Low illiq.	78.22%	18.49%	2.60%	0.41%	0.28%
2	16.73%	45.28%	27.65%	8.67%	1.68%
3	3.78%	22.83%	36.96%	28.48%	7.94%
4	1.09%	9.77%	24.07%	38.46%	26.61%
High illiq.	0.43%	3.12%	8.58%	24.35%	63.52%

Figure 2.1 Time-Series of the Illiquidity Measures

This figure plots the monthly cross-sectional means of *IlliqRKW* and *Gamma* over the period from January 2002 to December 2012. The illiquidity measures are defined in Table 2.1.





CHAPTER 3

EXPOSURE TO LIQUIDITY RISK AND EQUITY RETURNS IN BORSA ISTANBUL

3.1 Introduction

In finance, arbitrage pricing theory (APT), introduced by Ross (1976) shows that securities affected by systematic risk factors should earn risk premia in a risk-averse economy. Sensitivity to changes in each factor is represented by a factor-specific beta coefficient in APT. Although APT allows for the use of several risk factors that explain security returns, it does not have the ability to specify the factors ex ante. Illiquidity proxies are good candidates for the mentioned risk factors since unexpected variations in liquidity are able to affect firms' cash flows and investment opportunities.

A number of studies in the literature have been dedicated to investigating the relationship between illiquidity and stock returns. There are two different ways that liquidity can affect the asset returns. The first way is that liquidity being a characteristics of the asset returns. Secondly, liquidity can be thought as a separate risk factor. (e.g Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Lee, 2011). In this chapter, I consider liquidity as a separate risk factor. Acharya and Pedersen (2005) propose a liquidity-adjusted capital asset pricing model (LCAPM) and claim that if a stock's illiquidity moves inversely either with the market return or with the market liquidity, then that stock will have a significantly lower average return. The reason behind this conjecture is that investors are willing to pay more for stocks that allow them to exit at a proper cost during liquidity dry-ups. Lee (2011) examines an equilibrium asset pricing relation with liquidity both as a characteristics and as a risk factor in international markets and finds that liquidity risk is a priced factor in international financial markets. Moreover, Asparouhova et al. (2010) stress the importance of illiquidity measure selection by showing that the sensitivity of expected stock returns to different measures of liquidity and to the liquidity premium is biased towards finding a premium. Although there is an abundance of studies that examine stocks' exposure to systematic liquidity risk in U.S. markets, relatively little research has been conducted in non-U.S. markets.

The goal of this chapter is to further our understanding of liquidity exposure in the Turkish stock market. In this chapter, I furnish a better understanding of stocks' exposures to various illiquidity risk factors through univariate and multivariate estimates of factor betas and investigate the performance of these factor betas in predicting the cross-sectional variation in stock returns over the sample period. Following Bali et al. (2011), I first estimate factor betas using monthly stock returns, and then calculate the sensitivity of stock returns towards these factor betas. In other words, instead of the pricing ability of the factors, I test the pricing ability of the sensitivity coefficients on the factors. Therefore, if these financial factors indeed proxy for risk factors, stocks that are more sensitive to these factors ought to earn a compensation for risk in a risk-averse economy.

This study contributes to the literature in several ways. Central and Eastern European (CEE) markets have been under-investigated by previous literature. This chapter's first objective is to fill this gap by providing evidence on the pricing of sensitivity to liquidity in Borsa Istanbul, the largest CEE market. Second, while studying the role of liquidity, I pay attention to the issue pointed by Liu (2006) and Subrahmanyam (2010) regarding the robustness of research results to different liquidity metrics. I am not able use the microstructure data such as the bid-ask spread since it is not available for Turkey. Instead, I gather the widest range of illiquidity proxies that can be applied to Turkish markets to capture the multiple dimensions of liquidity risk using daily data.

I document that there exists a positive and significant link between stocks' betas towards illiquidity and expected equity returns for windows ranging from one to six months. The results are robust to the presence of book-to-market and size factors of Fama and French (1993) and the momentum factor of Carhart (1997) in the regression specification. Additionally, the results from the univariate portfolio analysis suggest that, on average, stocks with high illiquidity betas which are more sensitive to changes in illiquidity generate significantly and economically higher returns compared to stocks with low illiquidity betas. Hence, I conclude that the sensitivity to illiquidity is a priced risk factor in Turkish stock market.

The structure of the paper is as follows. Section 2 describes the data and the methodology used in the paper. Section 3 presents the empirical findings. Section 4 concludes.

3.2 Data and Description of Variables

In this chapter, I obtain equity returns and accounting data from Stockground.[15] The sample period is from January 1992 to December 2012. The stock price data is adjusted for stock splits, dividends and right offerings. Monthly stock returns are calculated by compounding the daily stock returns. Widely used financial factors are constructed for Borsa Istanbul by using the non-parametric portfolio analysis. The market factor (MKT) is measured as the monthly excess return of BIST-100 index. The book-to-market (*HML*) and size (*SMB*) factors of Fama and French (1993) are estimated by forming quintile portfolios every month using sorts of stocks on their book-to-market ratios and market values of equity, respectively. Then, the average monthly return differences between the highest and lowest quintile portfolios are calculated. The momentum factor (*UMD*) is constructed following Carhart (1997) as the return difference between the 30 percent of firms with the highest lagged six-month returns and the 30 percent of firms with the lowest lagged six-month returns. The portfolios are re-formed monthly. I use the illiquidity proxies that I explained in chapter 2.

Following Fama and French (1992), I match the accounting data for all fiscal year ends in calendar year j-1 with the returns and market values between July of year j and June of year j+1 to ensure that the accounting variables are known before the returns they are used to explain. To be included in the return tests for July of year j, a firm must have stock price

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[15] StockGround is a financial analysis software with advanced fundamental and technical analysis capabilities designed by Rasyonet Inc., a software solution provider to brokerage houses, commercial banks and portfolio management firms.

and market capitalization data for June of year *j* and book value of equity data for December of year *j*-1. It must also have monthly returns for at least 15 months during the 24 months preceding July of year *j* so that the beta estimates that are used in the Fama-MacBeth regressions can be calculated. Outliers, defined as stocks whose estimated illiquidity proxies in year *j*-1 are in the highest or lowest 1% tails of the distribution, are excluded. Following Jegadeesh and Titman (1993), momentum is defined as the lagged six-month cumulative return excluding the month prior to each monthly regression in order to eliminate the autocorrelation effect of monthly returns.

The primary objective of this chapter is to test the significance of the illiquidity risk factors' betas on predicting the cross-sectional variation in monthly stock returns. This goal can be reached by parametric tests and I conduct these tests to evaluate the predictive power of factor betas over future stock returns. In the first stage, for each individual stock, univariate and multivariate monthly time-series beta estimates of 10 different financial risk factors (factor betas) are calculated over a rolling-window period. In the second stage, Fama and MacBeth (1973) cross-sectional regressions of one-month as well as three- and six-month-ahead individual stock returns are utilized on the previously calculated factor betas for each month in the sample period. If the average slope coefficients from these Fama-MacBeth regressions show any statistical significance for certain financial factors, then I deduce that those factor betas have a significant predictive power over expected stock returns.

Table 3.1 presents descriptive statistics of firm-level stock returns and risk factors that are used in this chapter. Panel A reports the mean, median, standard deviation, minimum, maximum, 25th and 75th percentile, skewness and kurtosis statistics of the stock returns quoted in Borsa Istanbul for holding periods of one, three and six months. The average monthly stock return is 3.8%, surpassing the median return of 1.01%. The standard deviation of the monthly return is 20.01%. The return distribution is positively skewed and leptokurtic. Observe that similar patterns exist for 3- and 6-month return horizons. The statistics in Panel A, Table 3.1 reveal that stock returns have non-normal distribution. Panel B of Table 3.1 reports the descriptive statistics for Fama and French (1993) and Carhart (1997) momentum factors as well as six illiquidity factors. Observe that the *SMB* and *HML* factors have positive means of 0.0086 and 0.0026, respectively echoing the results of Cakici et al. (2013) regarding the effect of size and book-to-market in international markets. *SMB* and *HML* exhibit slight negative skewness. *UMD* has a negative mean of -0.0085, revealing the existence of reversal effect for equity returns in Borsa Istanbul. The Amihud illiquidity proxy (*Illiq*) and the log-transformed (*KLV*) versions of the Amihud measures have mean values of 35.3603 and 35.4224, respectively. Both of these measures are highly leptokurtic. The inflation-adjusted (*IlliqRKW*) Amihud measure has a mean of 0.5282, indicating that the absolute price change per million units of daily trading volume is approximately 53%. The mean-adjusted Amihud measure (*IlliqMA*) has a mean of 0.8932. *Illiqzero* displays a negative mean value of -1.7013. Pastor and Stambaugh (2003) reversal coefficient (*Gamma*) is highly leptokurtic with a mean (median) of 0.2972 (0.0006).

3.3 Empirical Results

3.3.1 Univariate Factor Betas in Cross-Sectional Regressions

This section conducts parametric (regression) tests to investigate the predictive power of factor betas over expected stock returns. In the first stage, univariate monthly factor betas are estimated for each stock from the univariate time-series regressions of stock returns on the risk factors over a 24-month rolling-window period. In the second stage, the cross-section of one-month as well as three- and six-month-ahead stock returns are regressed on the stocks' univariate factor betas each month during the period 1994-2012. In other words, the first two years of monthly stock returns from January 1992 to December 1993 are used to estimate the factor betas for each individual stock in the sample. Later, monthly rolling regression approach is utilized with a fixed estimation window of 24 months to generate the time-series monthly factor betas following the regression equation:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{F} \,.\; F_t + \varepsilon_{i,t} \tag{3.1}$$

where $R_{i,t}$ is the excess return on stock *i* in month *t* and F_t is one of the 10 financial risk factors in month *t*. $\alpha_{i,t}$ and $\beta_{i,t}^{F}$ are the alpha and the risk factor *F*'s beta for stock *i* in month *t*, respectively. In Eq. (3.1), I consider 10 variables as risk factors, including *MKT*, *SMB*, *HML, UMD, Illiq, IlliqRKW, IlliqMA, KLV, Illiqzero,* and *Gamma.* In other words, Eq. (3.1) consists of 10 regression equations where each regression is estimated for each risk factor separately.

Table 3.2 presents summary statistics for the factor betas obtained from the univariate time-series regressions of each factor on individual stock returns. β^{SMB} has a mean value of 0.1673 with a slightly positive skewness statistic of 0.3418. The average value of β^{HML} is 0.4565 with a standard deviation of 0.9626. β^{UMD} has a negative mean of -0.8964, β^{MKT} has a mean of 0.8644 and both have almost symmetrical distributions since the mean and median values are close. This inverse momentum effect is in contrast with the U.S. studies which show that momentum is positively related to stock returns. All of the univariate illiquidity factor betas have negative mean and median values with a negative skewness statistic. β^{Illiq}, $\beta^{IlliqRKW}$, β^{KLV} and $\beta^{Illiqzero}$ have negative mean values with negative 25th and 75th percentiles, indicating that there is a strong negative relationship between contemporaneous stock excess returns and these illiquidity betas. For $\beta^{IlliqMA}$ and β^{Gamma}, 75th percentiles are slightly positive indicating that most of the values are still in the negative territory and therefore the negative relationship between contemporaneous stock excess returns and *IlliqMA* as well as *Gamma* still holds.

In the second stage, starting from January 1994, Fama-MacBeth (1973) cross-sectional regressions of one-month as well as three- and six-month ahead individual stock excess returns are utilized on the univariate factor betas:

$$R_{i,t+n} = \omega_t + \lambda_t \,.\, \beta_{i,t}^{F} + \varepsilon_{i,t+n} \tag{3.2}$$

where $R_{i,t+n}$ is the cumulative excess return on stock *i* from month *t* to month *t+n* and $\beta_{i,t}^{F}$ is the risk factor F's beta for stock *i* in month *t* estimated using Eq. (3.1). ω_t and λ_t are the monthly intercepts and slope coefficients from the Fama and MacBeth (1973) regressions, respectively. Eq. (3.2) is also set of 10 regression equations where each regression equation is run for each financial risk factor beta separately. Tests of statistical significance are performed by using Newey-West (1987) methodology which corrects standard errors by taking the autocorrelation in the time-series of cross-sectional estimates into account.[16]

Table 3.3 presents the regression coefficients from Eq. (3.2) using the univariate factor betas as independent variables. The reported coefficients are time-series averages and the reported t-statistics are based on the time-series variation of regression coefficients. In Panel A, for one-month ahead stock returns, I obtain a positive and significant relation between four illiquidity betas and the expected stocks returns, namely for β^{Illiq}, $\beta^{IlliqRKW}$, $\beta^{IlliqMA}$, β^{KLV}. The average slope coefficients for these factor betas are 0.0542, 0.0007, 0.0011 and 0.0543 and the corresponding Newey-West adjusted t-statistics are 1.73, 2.00, 2.25 and 1.73, respectively. This result indicates that the positive and significant relation between illiquidity betas and expected stock returns is robust to illiquidity measure selection. Note that the sensitivity of future stock returns to illiquidity betas are more pronounced when $\beta^{IlliqRKW}$ and $\beta^{IlliqMA}$ are used as the independent variables.

In Panel B of Table 3.3, three-month-ahead returns are used as the dependent variable. In line with Panel A, the significant relation between illiquidity betas and expected stock returns persists for the four illiquidity proxies. The average slope coefficients from the regressions of three-month ahead equity returns on the previous month's *Illiq* and *IlliqRKW* betas are 0.2039 and 0.0024 with t-statistics of 2.02 and 2.18, respectively. Moreover, the average slope coefficient is significant at the 1% level when *IlliqMA* beta is used as the independent variable. Panel C of Table 3.3 shows the time-series average of the intercepts and slope coefficients from Eq. (3.2) using six-month ahead returns as the dependent variable. The results are consistent with the shorter time horizons. The average slope coefficients for the same four illiquidity betas (*Illiq, IlliqRKW, IlliqMA, KLV*) are positive and significant. The remaining six financial risk factor betas, including *MKT, SMB* and *HML* do not have any predictive power over expected stock returns regardless of the return horizon.

16 A lag of 6 is used for the Newey-West correction. Results are robust for several other choices.

3.3.2 Multivariate Factor Betas in Cross-Sectional Regressions

In the previous section, I have shown how strongly *Illiq, IlliqRKW, IlliqMA* and *KLV* betas predict the cross-sectional variation in equity returns. In this section, I drop other insignificant illiquidity factors from my analysis and focus only on the significant ones as well as the widely used market, size, book-to-market and Carhart (1997)'s momentum factors.

In the first stage, I run the following regression with a fixed rolling estimation window of 24-months to obtain the monthly time-series of multivariate factor betas:

$$R_{i,t}= \alpha_{i,t} +\beta_{i,t}^{MKT}.MKT_t+\beta_{i,t}^{SMB}.SMB_t+\beta_{i,t}^{HML}.HML_t \\ +\beta_{i,t}^{UMD}.UMD_t+\beta_{i,t}^{ILLIQ}.ILLIQ_t+\varepsilon_{i,t} \tag{3.3}$$

where $R_{i,t}$ is the excess return on stock *i* in month *t*, MKT_t, SMB_t, HML_t, UMD_t and $ILLIQ_t$ are the market, size, book-to-market, momentum factors and one of the four illiquidity proxies in month *t*, respectively. $\alpha_{i,t}$ is the alpha for stock *i* in month *t* and $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SMB}$, $\beta_{i,t}^{HML}$, $\beta_{i,t}^{UMD}$ and $\beta_{i,t}^{ILLIQ}$ are the market, size, book-to-market, momentum and illiquidity betas for stock *i* in month *t*, respectively.

In the second stage, monthly cross-sectional regressions are run for the following multivariate specification:

$$R_{i,t+n}=\omega_t+ \theta_t^{MKT}\beta_{i,t}^{MKT}+\theta_t^{SMB}\beta_{i,t}^{SMB}+\theta_t^{HML}\beta_{i,t}^{HML} \\ +\theta_t^{UMD}\beta_{i,t}^{UMD}+\theta_t^{ILLIQ}\beta_{i,t}^{ILLIQ}+\varepsilon_{i,t+n} \tag{3.4}$$

where $R_{i,t+n}$ is the cumulative excess return on stock *i* from month *t* to month *t+n* and $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SMB}$, $\beta_{i,t}^{HML}$, $\beta_{i,t}^{UMD}$, $\beta_{i,t}^{ILLIQ}$ are, respectively the market, size, book-to-market, momentum and illiquidity betas for stock *i* in month *t* estimated from Eq. (3.3). θ_t^{MKT}, θ_t^{SMB}, θ_t^{HML}, θ_t^{UMD} and θ_t^{ILLIQ} are the slope coefficients from the Fama and MacBeth (1973) regressions.

Table 3.4 presents the time-series averages of intercepts and slope coefficients from the Fama and MacBeth (1973) regressions of one-, three- and six-month-ahead equity returns on the four-factor model and one of the illiquidity betas. Controlling for other factors, I observe an insignificant relationship between β^{Illiq} and expected stock returns. $\beta^{IlliqRKW}$ exhibits a statistically significant predictive power for three- and six-month return horizons. Note that, there exists a statistically significant relation between $\beta^{IlliqMA}$ and expected stock returns and this positive and significant link persists regardless of the return horizon. The average slope coefficient on *IlliqMA* beta is estimated to be between 0.0029 and 0.0104 with Newey-West t-statistics ranging from 2.57 to 3.28. The average slope coefficient of HML beta is always positive; however, signs of the average slope coefficients of SMB and UMD betas alternate depending on the return horizon and the illiquidity proxies used. Moreover, aside from the illiquidity betas, only HML beta shows any significant predictive power and only for the one-month return horizon. All in all, Fama-MacBeth cross-sectional regressions, even after controlling for the market, size, book-to-market and momentum factors, provide strong evidence for a statistically significant positive relation between *IlliqMA* beta and future stock returns.

3.3.3 Univariate Portfolio Analysis of *IlliqMA* Beta

In the previous section, I show that the sensitivity of a stock's return towards mean-adjusted Amihud illiquidity proxy is a priced factor. Another method for examining the economical relation between illiquidity betas and expected stock returns is to use portfolio sorting. In this section, I use a non-parametric portfolio analysis where tercile portfolios are formed every month by sorting stocks based on their illiquidity beta metrics and one-month ahead returns are observed for each portfolio to see whether there exists a significant difference in future returns between stocks in the highest and lowest illiquidity beta portfolios. More specifically, portfolios are formed in each month between January 1994 and December 2012 by sorting stocks based on their illiquidity beta metrics where low $\beta^{IlliqMA}$ portfolio contains stocks with the lowest 30 percent illiquidity betas and high $\beta^{IlliqMA}$ portfolio contains stocks with the highest 30 percent illiquidity betas. The average one-month ahead returns are computed in each tercile to investigate whether there is a significant difference between the expected returns of the stocks in the high and low illiquidity beta terciles.

Table 3.5 presents the time-series averages of illiquidity betas and equal-weighted returns for each of these illiquidity beta-sorted portfolios. I should note that the average illiquidity beta of the low-beta portfolio is actually higher in absolute magnitude than the high-beta portfolio yet it is considered as a low-beta portfolio due to its negative sign. Observe that the average illiquidity beta is negative for both low- and medium-beta portfolios whereas the high-beta portfolio has a mean of 1.9897. The next-month average returns of the stocks in the low-beta and high-beta portfolios are 0.0344 and 0.0387, respectively. The difference between these two extreme terciles is equal to 0.0043 with a t-statistics of 4.44. This finding is also economically significant. Stocks in the high-beta portfolio yield about 5.16% higher annual returns compared to stocks in the low-beta portfolio. Therefore, the results in Table 3.5 strengthen the previous results that the sensitivity towards illiquidity is a priced risk factor in the Turkish stock market.

3.4 Conclusion

This chapter analyzes stocks' exposures to illiquidity risk factors through univariate and multivariate estimates of factor betas in explaining the cross-sectional variation in expected stock returns in Borsa Istanbul over the sample period between January 1992 and December 2012. This is the first sensitivity analysis of expected stock returns to factor loadings in the liquidity context for the Turkish stock market.

In this chapter, two tests are conducted for identifying the significance of illiquidity factor loadings on future equity returns. First, I utilize a two-step methodology. In the first step, monthly factor betas for each stock are computed using time-series regressions of individual stock returns on 10 distinct risk factors (6 illiquidity factors) over a 24-month rolling window period. In the second stage, I estimate parametric Fama-MacBeth cross-sectional regressions of one-, three- and six-month ahead equity returns on the stocks' univariate and multivariate factor betas computed in the first stage.

The univariate regression results reveal that there is a positive and significant relation between illiquidity betas and expected stock returns when *Illiq, IlliqRKW, IlliqMA* and *KLV* are used as the illiquidity variables. Controlling for the betas associated with the market, size, book-to-market and momentum factors does not affect the predictive power of *IlliqMA* beta. In other words, stocks that are more sensitive to illiquidity generate significantly higher future returns. Second, the results from the univariate portfolio analysis suggest that, on average, stocks with high illiquidity betas generate significantly and economically higher returns compared to stocks with low illiquidity betas. I, therefore, conclude that the sensitivity to illiquidity is a priced risk factor in Turkish stock market.

3.5 Tables

Table 3.1 Descriptive Statistics for Equity Returns and Financial Factors

This table presents summary statistics for equity returns and risk factors used in the study. Panel A reports the mean, median, standard deviation, minimum, maximum, 25th and 75th percentile, skewness and kurtosis statistics for individual equity returns for periods of one, three and six months constructed with daily individual security data listed in Borsa Istanbul over the period from January 1992 to December 2012. Statistics are computed as the time-series averages of the cross-sectional means. *SMB* is the Fama-French (1993) size factor. *HML* is the Fama-French (1993) book-to-market factor. *UMD* is the Carhart (1997) momentum factor. *MKT* is the monthly excess return of BIST-100 index. *Illiq* is the average of the daily ratio of the absolute return to the trading volume. *IlliqRKW* is the average of the daily ratio of the absolute return to the trading volume adjusted for inflation. *IlliqMA* is the mean-adjusted value of the average of daily ratio of the absolute return to the trading volume. *KLV* is the natural logarithm of one plus the average of the daily ratio of the absolute return to the trading volume. *Illiqzero* is the natural logarithm of the average of the daily ratio of the absolute return to the trading volume adjusted for no-trading days in a month. *Gamma* is the return reversal coefficient estimated using daily returns and volume data in a month, as in Pastor and Stambaugh (2003).

Table 3.1 (Continued)

Panel A: Individual Equity Returns

	Mean	Median	Std.Dev	Minimum	Maximum	25th Per	75th Per	Skewness	Kurtosis
1-month returns	0.0380	0.0101	0.2001	-0.4036	0.8214	-0.0755	0.1181	1.1495	5.7822
3-month returns	0.1273	0.0414	0.4180	-0.5714	1.9479	-0.1176	0.2649	1.7664	7.5710
6-month returns	0.2785	0.1010	0.7066	-0.6513	3.5500	-0.1380	0.4706	2.1738	9.1331

Panel B: Financial Factors

	Mean	Median	Std.Dev	Minimum	Maximum	25th Per	75th Per	Skewness	Kurtosis
SMB	0.0086	0.0079	0.0719	-0.2210	0.2157	-0.0316	0.0489	-0.0839	4.1547
HML	0.0026	0.0029	0.0606	-0.2069	0.1832	-0.0309	0.0346	-0.0661	4.7644
UMD	-0.0085	0.0012	0.0594	-0.2007	0.1272	-0.0346	0.0275	-0.8778	4.3893
MKT	0.0003	0.0072	0.1229	-0.3013	0.4445	-0.0828	0.0676	0.4280	4.6472
Illiq	35.3603	0.1120	209.0454	0.0005	1815.4210	0.0210	1.0788	7.4840	60.5323
IlliqRKW	0.5282	0.0350	2.1084	0.0003	16.5581	0.0100	0.1370	6.1358	42.8615
IlliqMA	0.8932	0.1412	2.4056	0.0006	16.8729	0.0304	0.6037	4.8658	28.8858
KLV	35.4224	0.1120	209.4906	0.0005	1820.7500	0.0210	1.0796	7.4892	60.6247
Illiqzero	-1.7013	-2.1921	3.1220	-7.5935	8.4309	-3.8638	0.0759	0.7854	3.7143
Gamma	0.2972	0.0006	6.9550	-35.1504	50.2308	-0.0073	0.0191	2.8200	37.7794

Table 3.2 Descriptive Statistics for Univariate Factor Betas

This table reports the mean, median, standard deviation, minimum, maximum, 25th and 75th percentile, skewness and kurtosis statistics for univariate monthly factor betas that are estimated using the univariate time-series regressions of individual equity returns on each financial factor for the sample period 1992-2012. The financial factors are described in Table 3.1.

	Mean	Median	Std.Dev	Minimum	Maximum	25th Per	75th Per	Skewness	Kurtosis
β^{SMB}	0.1673	0.1471	0.8349	-1.8544	2.8285	-0.3608	0.6440	0.3418	3.7261
β^{HML}	0.4565	0.4085	0.9626	-2.0729	3.2735	-0.1391	1.0100	0.2320	3.5344
β^{UMD}	-0.8964	-0.9124	1.1341	-3.9825	2.1718	-1.5799	-0.2015	-0.0023	3.3605
β^{MKT}	0.8644	0.8653	0.3818	-0.1472	1.8578	0.6275	1.1062	-0.0294	3.1840
β^{Illiq}	-2.6740	-0.1656	8.4253	-57.7780	5.3830	-1.2328	-0.0074	-4.7327	27.3956
$\beta^{IlliqRKW}$	-5.2221	-0.6397	15.1934	-103.5519	10.5542	-3.0249	-0.0759	-4.6140	26.4758
$\beta^{IlliqMA}$	-0.6287	-0.0348	3.1911	-22.6017	8.1018	-0.3041	0.0126	-4.4595	30.2739
β^{KLV}	-2.6634	-0.1656	8.3853	-57.4630	5.4728	-1.2325	-0.0074	-4.7234	27.3093
$\beta^{Illiqzero}$	-0.0599	-0.0558	0.0545	-0.2156	0.0930	-0.0919	-0.0257	-0.2180	3.5915
β^{Gamma}	-1.2872	-0.0357	16.5406	-96.0884	72.9145	-1.0679	0.2107	-1.5423	20.3107

Table 3.3 Univariate Fama-MacBeth Regressions of Stock Returns on Factor Betas

This table reports the time-series averages of the intercepts and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of future individual stock returns on univariate factor betas for the sample period 1992-2012. In the first stage, monthly factor betas are estimated for each stock over a 24-month rolling-window period. In the second stage, the cross-section of one-month as well as three- and six-month-ahead stocks' excess returns are regressed each month on univariate factor betas. Newey-West (1987) t-statistics are reported in parentheses. The financial factors are described in Table 3.1. Panels A, B and C present results for return horizons of one, three and six months, respectively.

Panel A: 1-month returns

Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}	$\beta^{IlliqRKW}$	$\beta^{IlliqMA}$	β^{KLV}	$\beta^{Illiqzero}$	β^{Gamma}
0.0380	0.0061									
(4.07)	(1.20)									
0.0427		0.0008								
(4.36)		(0.32)								
0.0415			0.0026							
(4.24)			(1.54)							
0.0422				-0.0007						
(4.14)				(-0.42)						
0.0444					0.0542					
(4.35)					(1.73)					
0.0445						0.0007				
(4.35)						(2.00)				
0.0444							0.0011			
(4.29)							(2.25)			
0.0444								0.0543		
(4.35)								(1.73)		
0.0445									0.0123	
(4.31)									(0.65)	
0.0431										-0.0057
(4.25)										(-0.35)

Panel B: 3-month returns

Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}	$\beta^{IlliqRKW}$	$\beta^{IlliqMA}$	β^{KLV}	$\beta^{Illiqzero}$	β^{Gamma}
0.1267	0.0204									
(4.39)	(1.34)									
0.1348		0.0044								
(4.22)		(0.62)								
0.1323			0.0095							
(4.26)			(1.44)							
0.1413				0.0003						
(4.30)				(0.05)						
0.1485					0.2039					
(4.48)					(2.02)					
0.1483						0.0024				
(4.46)						(2.18)				
0.1478							0.0034			
(4.44)							(2.50)			
0.1485								0.2032		
(4.47)								(2.02)		
0.1500									0.0758	
(4.38)									(1.13)	
0.1487										0.0546
(4.44)										(1.03)

Table 3.3 (Continued)

Panel C: 6-month returns										
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}	$\beta^{IlliqRKW}$	$\beta^{IlliqMA}$	β^{KLV}	$\beta^{Illiqzero}$	β^{Gamma}
0.2664	0.0516									
(4.55)	(1.53)									
0.2852		0.0068								
(4.25)		(0.53)								
0.2878			0.0153							
(4.48)			(1.00)							
0.3116				0.0063						
(4.54)				(0.55)						
0.3222					0.4113					
(4.61)					(2.06)					
0.3221						0.0048				
(4.59)						(2.22)				
0.3221							0.0076			
(4.56)							(2.58)			
0.2911								0.3325		
(4.27)								(2.09)		
0.3275									0.1810	
(4.54)									(1.25)	
0.3230										0.2223
(4.57)										(1.49)

Table 3.4 Multivariate Regressions of Expected Stock Returns on Carhart's (1997) Four Factors and Illiquidity Betas

This table reports the time-series averages of the intercepts and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of future individual stock returns on multivariate factor betas for the sample period 1992-2012. In the first stage, monthly factor betas are estimated for each stock from multivariate time-series regressions of stock returns on the selected factors. In the second stage, the cross-section of one-month as well as three- and six-month-ahead stocks' excess returns are regressed each month on the factor betas. Newey-West (1987) t-statistics are reported in parentheses. The factor betas are defined in Table 3.1. Panels A, B, C and D present results for β^{Illiq}, $\beta^{IlliqRKW}$, $\beta^{IlliqMA}$, β^{KLV}, respectively.

Panel A:

		1-month returns			
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}
0.0412	0.0030	-0.0010	0.0026	0.0004	-0.0014
(4.46)	(0.86)	(-0.47)	(1.88)	(0.25)	(-0.20)

		3-month returns			
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}
0.1369	-0.0034	0.0043	0.0063	-0.0008	0.0123
(4.68)	(-0.29)	(0.59)	(1.09)	(-0.17)	(0.54)

		6-month returns			
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}
0.2849	0.0012	0.0068	0.0132	-0.0046	0.1102
(4.76)	(0.06)	(0.51)	(0.89)	(-0.51)	(1.47)

Panel B:

		1-month returns			
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqRKW}$
0.0463	0.0028	-0.0010	0.0027	0.0005	0.0001
(4.48)	(0.76)	(-0.47)	(1.98)	(0.38)	(0.34)

		3-month returns			
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqRKW}$
0.1363	-0.0023	0.0031	0.0093	-0.0013	0.0008
(4.57)	(-0.20)	(0.45)	(1.68)	(-0.29)	(1.67)

		6-month returns			
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqRKW}$
0.2875	-0.0010	0.0050	0.0210	-0.0048	0.0029
(4.64)	(-0.04)	(0.38)	(1.47)	(-0.53)	(2.28)

Table 3.4 (Continued)

Panel C:

1-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqMA}$
0.0415	0.0041	-0.0022	0.0026	0.0005	0.0029
(4.29)	(0.97)	(-1.04)	(2.02)	(0.30)	(2.57)

3-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqMA}$
0.1299	0.0113	-0.0041	0.0074	-0.0017	0.0070
(4.54)	(0.92)	(-0.62)	(1.49)	(-0.35)	(3.28)

6-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqMA}$
0.2755	0.0249	-0.0080	0.0176	-0.0043	0.0104
(4.77)	(1.07)	(-0.67)	(1.31)	(-0.47)	(2.59)

Panel D:

1-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{KLV}
0.0412	0.0031	-0.0010	0.0026	0.0003	-0.0018
(4.46)	(0.84)	(-0.47)	(1.89)	(0.22)	(-0.25)

3-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{KLV}
0.1369	-0.0033	0.0042	0.0065	-0.0008	0.0105
(4.68)	(-0.29)	(0.58)	(1.12)	(-0.18)	(0.45)

6-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{KLV}
0.2849	0.0012	0.0067	0.0133	-0.0047	0.1107
(4.77)	(0.06)	(0.50)	(0.90)	(-0.52)	(1.48)

Table 3.5 Univariate Portfolios of Stock Returns sorted by $\boldsymbol{\beta^{IlliqMA}}$

This table presents return comparisons between equity portfolios formed based on *IlliqMA* beta. The portfolios are formed in each month between January 1994 and December 2012. Low $\beta^{IlliqMA}$ portfolio contains stocks with the lowest 30 percent *IlliqMA* betas and high $\beta^{IlliqMA}$ portfolio contains stocks with the highest 30 percent *IlliqMA* betas. The last row shows the differences of monthly returns between the high-beta and low-beta portfolios. Newey-West (1987) adjusted t-statistics are presented in parenthesis.

Portfolios	$\beta^{IlliqMA}$	Next-month average returns
Low $\beta^{IlliqMA}$	-4.1352	0.0344
Medium $\beta^{IlliqMA}$	-0.0848	0.0410
High $\beta^{IlliqMA}$	1.9897	0.0387
High $\beta^{IlliqMA}$ - Low $\beta^{IlliqMA}$		0.0043 (4.44)

REFERENCES

Acharya, V., Pedersen L.,2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77, 375-410.

Akdeniz, L., Altay-Salih, A., Aydogan, K., 2000. A cross-section of expected stock returns on the Istanbul Stock Exchange. *Russian & East European Finance & Trade* 36, 6-26.

Akdeniz, L., Altay-Salih, A., Umutlu, M., 2013. Foreign equity trading and average stock-return volatility. *The World Economy* 36, 1209-1228.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time series effects. *Journal of Financial Markets* 5, 31-56.

Amihud, Y., Mendelson H., 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17, 223-249.

Asparouhova, E., Bessembinder, H., Kalcheva, I., 2010. Liquidity biases in asset pricing tests. *Journal of Financial Economics* 96, 215-237.

Atilgan, Y., Demirtas, K. O., Erdogan, A., 2015. Macroeconomic factors and equity returns in Borsa Istanbul. *İktisat Isletme ve Finans* 30, 9-30.

Bali, T. G., Brown, S. J., Caglayan, M. O., 2011. Do hedge funds' exposures to risk factors predict their future returns? *Journal of Financial Economics* 101, 36-68.

Bali, T. G., Peng, L., Shen, Y., Tang, Y., 2014. Liquidity shocks and stock market reactions. *Review of Financial Studies* 27, 1434-1485.

Bali, T. G., Cakici, N., 2008. Idiosyncratic volatility and the cross-section of expected returns. *Journal of Financial and Quantitative Analysis* 43, 29-58.

Bali, T. G., Cakici, N., Fabozzi, F. J., 2013. Book-to-market and the cross-section of expected returns in international stock markets. *Journal of Portfolio Management* 39, 101-115.

Bali, T. G., Cakici, N., Yan, X., Zhang, Z., 2005. Does idiosyncratic risk really matter? *Journal of Finance* 60, 905-929.

Barinov, A., 2014. Turnover: liquidity or uncertainty? *Management Science* 60, 2478-2495.

Batten, J., Vo, X. V., 2014. Liquidity and return relationship in an emerging market. *Emerging Markets Finance and Trade* 50, 5-21.

Bekaert, G., Harvey, C., Lundblad, C., 2007. Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies* 20, 1783-1831.

Ben-Rephael, A., Kadan, O., Wohl, A., 2015. The diminishing liquidity premium. *Journal of Financial and Quantitative Analysis* 50, 197-229.

Brennan, M., Subrahmanyam, A., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics* 41, 441-464.

Brennan, M., Huh, S.-W., Subrahmanyam, A., 2013. An Analysis of the Amihud Illiquidity Premium. *The Review of Asset Pricing Studies* 3 (1), 133-176.

Brockman, P., Chung, D. Y., Perignon, C., 2009. Commonality in liquidity: a global perspective. *Journal of Financial and Quantitative Analysis* 44, 851-882.

Brunnermeier, M., Pedersen, L., 2009. Market liquidity and funding liquidity. *Review of Financial Studies* 22, 2201-2238.

Cakici, N., Fabozzi, F. J., Tan, S., 2013. Size, value and momentum in emerging market stock returns. *Emerging Markets Review* 16, 46-65.

Carhart, M. M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.

Chan, H. W., Faff, R. W., 2005. Asset pricing and illiquidity premium. *Financial Review* 40, 429-458.

Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. *Journal of Financial Economics* 56, 3-28.

Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity. *Journal of Finance* 56, 501-530.

Chordia, T., Roll, R., Subrahmanyam, A., 2002. Order imbalance, liquidity, and market returns. *Journal of Financial Economics* 65, 111-130.

Cooper, S. K., Goth, J. C., Avera, W. E., 1985. Liquidity, exchange listing and common stock performance. *Journal of Economics and Business* 37, 19-33.

Datar, V. T., Naik, N., Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. *Journal of Financial Markets* 1, 203-219.

Eleswarapu, V. R., 1997. Cost of transacting and expected returns in the Nasdaq market. *Journal of Finance* 52, 2113-2127.

Eleswarapu, V., Reinganum, M., 1993. The seasonal behavior of liquidity premium in asset pricing. *Journal of Financial Economics* 34, 373-386.

Fama, E., French, K., 1992. The cross-section of expected stock returns. *Journal of Finance* 47, 427-465.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Fama, E., MacBeth, J. D., 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81, 607-636.

Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica* 57, 1121-1152.

Glosten, L., Harris, L., 1988. Estimating the components of the bid–ask spread. *Journal of Financial Economics* 21, 123-142.

Goyenko, R., Holden, C., Trzcinka, C., 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 92, 153-181.

Hameed, A., Kang, W., Viswanathan, S., 2010. Stock Market Declines and Liquidity. *Journal of Finance* 65, 257-293.

Hasbrouck, J., Seppi, D. J., 2001. Common factors in prices, order flows, and liquidity. *Journal of Financial Economics* 59, 383-411.

Imisiker, S., Tas, B. K. O., 2013. Which firms are more prone to stock market manipulation? *Emerging Markets Review* 16, 119-190.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 65-91.

Kang, W., Zhang, H., 2014. Measuring liquidity in emerging markets. *Pacific-Basin Finance Journal* 27, 49-71.

Karolyi, G. A., Lee, K.-H., van Dijk, M. A., 2012. Understanding commonality in liquidity around the world? *Journal of Financial Economics* 105, 82-112.

Korajczyk, R. A., Sadka, R., 2008. Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics* 87, 45-72.

Kyle, A., 1985. Continuous auctions and insider trading. *Econometrica* 53, 1315-1335.

Lam, K. S. K., Tam, L. H. K., 2011. Liquidity and asset pricing: evidence from the Hong Kong stock market. *Journal of Banking and Finance* 35, 2217-2230.

Lee, K.-H., 2011. The world price of liquidity risk. *Journal of Financial Economics* 99, 136-161.

Lesmond, D., 2005. Liquidity of emerging markets. *Journal of Financial Economics* 77, 411-452.

Lesmond, D., Ogden, J., Trzcinka, C., 1999. A new estimate of transaction costs. *Review of Financial Studies* 12, 1113-1141.

Litzenberger, R.H., Ramaswamy, K., 1979. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *Journal of Financial Economics* 7, 163-195.

Liu, W., 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics* 82, 631-671.

Lo, A. W., Wang, J., 2000. Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory. *The Review of Financial Studies* 13, 257-300.

Marshall, B. R., 2006. Liquidity and stock returns: Evidence from a pure order-driven market using a new liquidity proxy. *International Review of Financial Analysis* 15, 21-38.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703-708.

Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642-685.

Roll, R., 1984. A simple Implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39, 1127-1139.

Ross, S. A., 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory 13*, 341-360.

Sadka, R. 2006. Momentum and post-earnings-annoucement drift anomalies: the role of liquidity risk. *Journal of Financial Economics* 80, 309-349.

Subrahmanyam, A., 2010. The cross-section of expected stock returns: What have we learned from the past twenty-five years of research? *European Financial Management* 16, 27-42.

Vaihekoski, M., 2009. Pricing of liquidity risk: empirical evidence from Finland. *Applied Financial Economics* 19, 1547-1557.

Watanabe, A., Watanabe, M., 2008. Time-varying liquidity risk and the cross section of stock returns. *Review of Financial Studies* 21, 2449-2486.

Yuksel, A., Yuksel, A., Doganay, M., 2010. İstanbul Menkul Kıymet Borsasında işlem gören hisse senetlerinin fiyatlandırılmasında likiditenin rolü. *İktisat, İşletme ve Finans*, 25(293), 69-94.